



Comprehensive Report on AU Students Research Output 2024-2025

AU Scientific Research Center



Abstract

The concept of incorporating undergraduate students in research activities of a university is exciting – particularly for colleges or universities that mainly offer undergraduate programs. As part of AU role towards building capacity of its students in research, AU has engaged its senior undergraduate students in research via courses and capstone projects that address industrial problems sponsored by local industry. Additionally, students are encouraged to become coresearchers with faculty on research projects. This allows them to experience firsthand the translation of theoretical work into applied research and help them decide on a career path. This research often involves teamwork and in-depth interaction with colleagues which improve students' communication skills that are increasingly sought after by employers. A total of 11 documents have been published by AU students in association with AU faculty for 2024/2025 academic year (8 Journal and 3 Conference). Many of these publications were in Q journals (Q1: 6; Q2: 2; Q3: 0, Q4: 0, and No-Quartile: 0).

AU Students Research Output

Engaging in undergraduate research represents a transformative learning experience that profoundly enriches a student's journey through their undergraduate education. The impact of participating in research, scholarship, or creative endeavors extends far beyond the classroom, making it a cornerstone of an enriched undergraduate experience. Australian University (AU) has been a strong proponent of fostering this research culture among its undergraduate students, providing them with opportunities to collaborate with faculty members on various research projects integrated into their courses and culminating in capstone experiences. Participating in undergraduate research yields a multitude of advantages for students. Beyond the acquisition of knowledge within the classroom, students find that involvement in research extends their learning by broadening and deepening their understanding of their chosen field of study. Through this hands-on engagement, they acquire a diverse set of skills, which encompass critical thinking, problem-solving, data analysis, and effective communication.

One of the most significant benefits of undergraduate research is its capacity to serve as a compass, helping students navigate their academic and career aspirations. By immersing themselves in research early in their academic journey, undergraduates gain a unique insight into their personal interests and inclinations. This revelation often ignites a passion for research, prompting many to pursue advanced degrees and even faculty positions in academia. In essence, the experience not only facilitates informed decision-making about their career path but also empowers them to chart a course that aligns with their evolving academic and professional interests.

The current effects of AU's dedication to promoting undergraduate research are profound, nurturing a culture of academic curiosity and providing productive ground for the next generation of researchers and scholars. Through these research opportunities, students embark on a transformative educational journey, setting the stage for lifelong learning, innovation, and the advancement of knowledge. Australian University's unwavering commitment to fostering undergraduate research continues to shape the future by nurturing the intellectual growth and career aspirations of its students. A total of **11** documents have been published by AU students in association with AU faculty for 2024/2025 academic year as shown in Figures 1 and 2. Figures 1 and 2 show the distribution of these journals by discipline as well their impact, respectively.

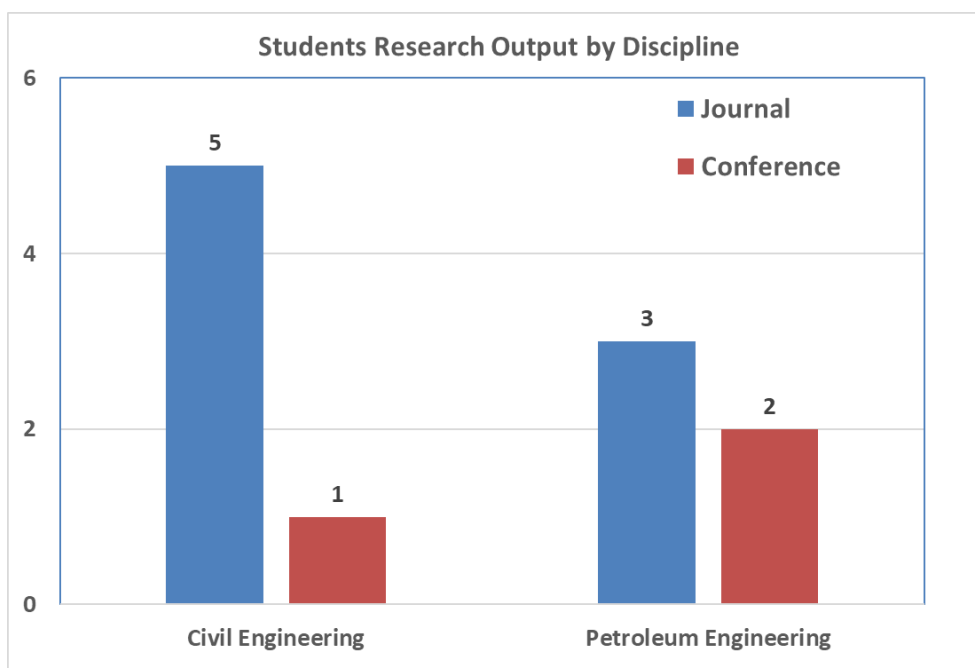


Figure 1. AU Students Research Outcome by Discipline (2024-2025)

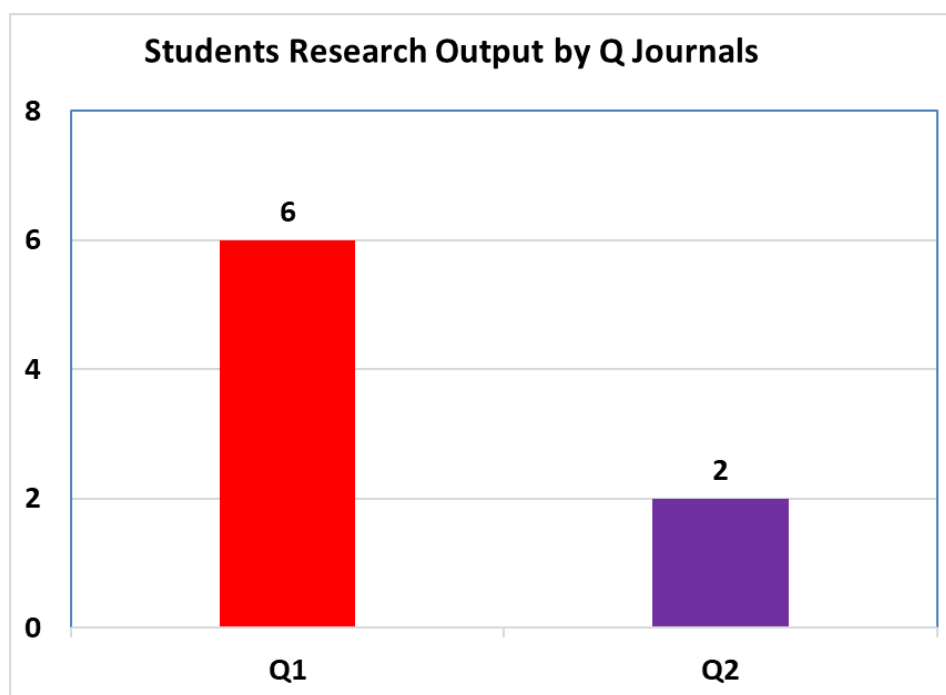


Figure 2. AU Students Research Outcome in Q Journals (2024-2025)

List of Publications

1 Students Research

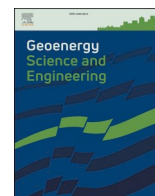
Publications of College of Engineering					
Sr. التسلسل	Authors المؤلف	Publication Title عنوان النشر	Name of Journal/ Conference اسم المجلة/المؤتمر	Category / Impact Factor الفئة / عامل التأثير	Date التاريخ
Civil Engineering Department					
1.	Masoud Irannezhad, Zahrah Abdulghafour, Retaj AlQallaf, Fadak Abdulreda, Ghadeer Shamsah, Hajar Alshammari	Variations and Trends in 115 Years of Graded Daily Precipitation Records at Three Hydrometeorological Stations in Finland.	Water (MDPI)	Journal (Q1: Impact Factor: 3.27)	18/9/2024
2.	Rana Malhas, Sara Salah, Mariam Alawadhi	Utilizing eco-friendly shredded waste tires for oil spill cleanup: Adsorption isotherm and kinetic studies	Journal of Environmental Chemical Engineering	Journal (Q1: Impact Factor: 7.8)	9/3/2025
3.	Masoud Irannezhad, Zahrah Abdulghafour, Amin Sadeqi	Climate teleconnections influencing historical variations, trends, and shifts in snow cover days in Finland	Earth Systems and Environment	Journal (Q1: Impact Factor: 6.65)	3/9/2024
4.	Masoud Irannezhad, Zahrah Abdulghafour, Hannu Marttila	Annual and seasonal mean daily discharge in natural and regulated rivers in Northern Finland: variability, trends, and links to climate teleconnections	Hydrology Research	Journal (Q2: Impact Factor: 2.7)	6/9/2024
5.	Mohamed Salem, Ruqaya S. Al-Sabah, Mohamed T. Elnabwy, Emad Elbeltagi and Mohamed Tantawy	Critical Success Factors for the Widespread Adoption of Virtual Alternative Dispute Resolution (VADR) in the Construction Industry: A Structural Equation Modeling Analysis	Buildings	Journal (Q2: Impact factor: 3.57)	16/9/2024

Publications of College of Engineering					
Sr. التسلسل	Authors المؤلف	Publication Title عنوان النشر	Name of Journal/ Conference اسم المجلة/المؤتمر	Category / Impact Factor الفئة / عامل التأثير	Date التاريخ
6.	Masoud Irannezhad, Zahrah Abdulghafour	Climate Teleconnections Influencing Desertification in the Lancang-Mekong River Basin	The 10th International Conference on Water Resource and Environment 2024 (WRE2024) Published in “WRE 2024 Proceeding- book series Lecture Notes in Civil Engineering”	Conference	15- 18/12/2024
Petroleum Engineering Department					
1.	Biltayib Misbah, Rida Elgaddafi, Rana N. Malhas, Suad Al Radhwan, Asama Hussain, Ali Hersi	Exploring the rheology characteristics of Flowzan and Xanthan polymers in drilling water based fluids at high-temperature and high-shear rates	Geoenergy Science and Engineering	Journal (Q1: Impact Factor: 5.3)	7/9/2024
2.	Jean H El Achkar, Suad Al Radhwan, Ahmed M Al-Otaibi, Abdul Md Mazid	Optimizing food waste anaerobic digestion in Kuwait: Experimental insights and empirical modelling using artificial neural networks	Waste Management & Research	Journal (Q1: Impact Factor: 4.6)	5/10/2024
3.	Jean H. El Achkar, Rana Malhas , Faisal Albalool , Abdullah Alrabaie	Sustainable conversion of petroleum sludge to methane: A study on anaerobic biodegradability in batch and continuous systems	Geoenergy Science and Engineering	Journal (Q1: Impact Factor: 5.3)	4/3/2025
4.	K. W. Amadi; R. M Elgaddafi; M. A AlAli; A. M Dashti	Reconstructing Missing and Non-Recorded Well Log Data Using Machine Learning Techniques	Mediterranean Offshore Conference, Alexandria, Egypt, October 20, 2024	Conference	20/10/2024

Publications of College of Engineering					
Sr. التسلسل	Authors المؤلف	Publication Title عنوان النشر	Name of Journal/ Conference اسم المجلة/المؤتمر	Category / Impact Factor الفئة / عامل التأثير	Date التاريخ
5.	RM Elgaddafi, K Amadi, BM Biltayib, MT Al Saba, M Omar, A Dashti, M Alali, M Alabdullah	Towards Autonomous Rotary Drilling System: A Robust Rate of Penetration Model for Drilling Operation Using Artificial Intelligence	SPE Conference at Oman Petroleum & Energy Show, Muscat, Oman, May 2025	Conference	1/5/2025

AU Students Research Output in Q-Journals		
Sr. التسلسل	Quartile (From Scopus)	Number of Published Journal Papers عدد البحوث المنشورة
1.	Q1	6
2.	Q2	2
3.	Q3	0
4.	Q4	0
5.	No Quartile	0
Grand Total		8





Exploring the rheology characteristics of Flowzan and Xanthan polymers in drilling water based fluids at high-temperature and high-shear rates

Biltayib Misbah^{a,*}, Rida Elgaddafi^a, Rana N. Malhas^a, Suad Al Radhwan^a, Asama Hussain^b, Ali Hersi^a

^a Department of Petroleum Engineering, College of Engineering, Australian University, Kuwait

^b Department of Electrical Engineering, College of Engineering, Australian University, Kuwait

ARTICLE INFO

Keywords:

Drilling fluids
Flowzan polymer
Taylor-Couette system
Viscometer
Xanthan polymer

ABSTRACT

The study of drilling fluid behaviour across various temperature conditions is of paramount importance for industries such as oil and gas extraction, mineral exploration, and large-scale construction projects. To address this need, a custom-designed viscometer known as the Australian University of Kuwait Taylor-Couette System (AUTCS) was developed. The AUTCS apparatus incorporates a Taylor-Couette system, consisting of two co-axial cylinders with a testing liquid capacity of 100 ml. The inner cylinder can be rotated at speeds ranging from 0 to 3000 rpm. This configuration provides an economical testing system that is particularly suitable for studying expensive drilling fluids. To investigate high-temperature (HT) conditions, the apparatus is equipped with a controllable heating film jacket capable of warming fluids up to 350 F. One specific area of interest in the drilling industry is the exploration of less commonly used polymers, such as Flowzan and Xanthan, in water-based mud (WBM). Flowzan has gained increasing attention due to its potential applications in drilling fields. To facilitate the study of Flowzan and Xanthan, the AUTCS viscometer was fine-tuned using the standard conventional lab viscometer, FANN, that has limitations in terms of rotational speed range (0–600 RPM) and temperature range. The rheology characteristics of Flowzan and Xanthan including consistency charts, viscosity, and darcy friction factor are obtained and presented at temperatures of 79 F, 104 F, and 150 F, across a range of speeds from 0 to 3000 RPM. The findings were examined across several correlation functions. It is found that the Herschel–Bulkley model best represent Flow Zan and Xanthan polymers. These correlations contribute to a comprehensive understanding of the new polymers' performance under different temperature and speed conditions in drilling applications.

1. Introduction

Drilling operations are essential in industries like oil and gas exploration, mineral extraction, and geotechnical engineering. They involve creating boreholes to access resources or collect geological data, with varying complexity based on factors such as depth and geological conditions. Drilling technologies have evolved from manual methods to advanced rotary drilling systems, enhancing resource extraction capabilities (Teodoriu and Bello, 2021). High-pressure and high-temperature (HPHT) conditions in deep drilling impact cement's rheological properties, affecting setting times and viscosity (Wang et al., 2012).

The drilling industry seeks fluids with improved mechanical, physical, chemical, and thermal properties, essential for high-temperature environments exceeding 300 F (Phi et al., 2019); (Misbah et al.,

2023). High temperatures affect the mechanical properties of formations, tool wear, and fluid performance, challenging drilling efficiency and safety (Shadravan and Amani, 2012). Research focuses on understanding fluid behaviour at elevated temperatures, leading to specialized formulations for stability and effectiveness under extreme conditions (Galindo et al., 2015).

Environmentally and economically, optimizing drilling fluids in high-temperature wells reduces risks like blowouts and wellbore instability, and minimizes equipment wear and nonproductive time. Successful management of drilling fluid properties is crucial for operational success in the challenging environments of high-temperature wells (Ezell and Harrison, 2008).

Fluid dynamics studies, from laminar to turbulent flows, are key in drilling operations. Customizing fluid properties, such as viscosity and

* Corresponding author.

E-mail address: b.biltayib@au.edu.kw (B. Misbah).

<https://doi.org/10.1016/j.geoen.2024.213309>

Received 18 February 2024; Received in revised form 3 September 2024; Accepted 7 September 2024

Available online 12 September 2024

2949-8910/© 2024 Published by Elsevier B.V.

density, can reduce equipment wear and stabilize wellbores (Sayindla et al., 2019; Biltayib et al., 2018). Understanding the rheological properties, behaviour and parameters of drilling fluid, using devices like FANN viscometer, including the Plastic viscosity PV, apparent viscosity (AV), yield point (YP), flow index (n), consistency index (k), density, fluid loss, gel strength, and regime of drilling fluids, are critical for effective hole cleaning during drilling operations flow regimes (Al-Rubaii, 2023).

Utilizing a device capable of operating at speeds ranging from 0 to 3000 RPM allows for a detailed examination of the viscosity-shear rate relationship in both water-based mud (WBM) and oil-based mud (OBM) drilling fluids. In the case of WBM, an increase in shear rate usually leads to a reduction in viscosity, a characteristic of non-Newtonian, shear-thinning fluids, as described in the "Petroleum Engineering Handbook" by the Society of Petroleum Engineers (Lake, 2019); (Rashidi et al., 2021). Conversely, OBM displays more intricate behaviour owing to its oil content, leading to varying viscosity responses at different shear rates, a phenomenon detailed in "Drilling Fluids Processing Handbook" by Elsevier (Drilling Fluids Processing Handbook, 2005). Understanding these behaviours is crucial for tailoring fluid properties to specific drilling scenarios. Moore and Young's research, (Yousuf et al., 2021), emphasizes the impact of shear rates on drilling fluid efficiency and performance.

An upgraded AUTCS was developed at Australian University of Kuwait, which is an enhanced version of the model mentioned in Rashidi et al. (2020). This AUTCS is capable of handling up to 100 ml of fluid and is distinguished by its wide operational range, with circular speeds that can be adjusted from 0 to 3000 RPM. A key feature of this device is its integrated controllable thermal jacket, enabling us to heat the fluid up to 300 F. This allows for a comprehensive examination of drilling fluid properties across a broad spectrum of temperatures and flow conditions, including both laminar and turbulent flows.

Our experiments were meticulously conducted using the AUTCS at various speeds, exploring the full range up to 3000 RPM. Two commonly utilized polymers in water-based mud (WBM) were studied examining their behaviour under a diverse array of speeds and temperature conditions. To calibrate the AUTCS, readings were obtained from a standard FANN laboratory viscometer, ensuring the same polymers were tested under identical conditions.

The findings from these extensive experiments, which effectively utilized the wide-ranging speed and temperature capabilities of AUTCS, offer detailed insights into the behaviour of drilling fluids in HTHP conditions.

1.1. Background on HPHT wells

As global demand for hydrocarbons is rising fast, the oil and gas industries have been forced to explore reservoirs in more challenging conditions, characterized by high-pressure, high-temperature conditions. This trend is leading to rise the number of drilling wells in HPHT environment. According to the market for drilling fluids and completion fluids was estimated at \$8.1 billion in 2020 and is expected to increase at a compound annual growth rate of 3.8 % from 2021 to 2030, reaching \$11.7 billion by 2030 valued at \$8.1 billion in 2020, is expected to grow at a 3.8% annual rate, reaching \$11.7 billion by 2030 (Davoodi et al., 2023). Therefore, necessitates advancements in improved technology, material selection and testing procedures are needed to overcome the common problems in these conditions (Nikolaev and Tabatabaee Moradi, 2016).

The HPHT conditions have been well defined by UK Continental shelf operations, when bottomhole temperature exceeds 300F and bottom-hole pressure exceeds 10,000 psi (Shadravan and Amani, 2012; Salim and Amani, 2013). Although numerous of the high-pressure, high-temperature (HPHT) wells have been drilled in different parts of the world, these types of wells.

Still present a drilling challenge because technologies for monitoring

downhole pressure and temperatures are not well developed (Teodoriu and Bello, 2021). So, the technical concept in HPHT drilling is substantial to design the tools for the key planning processes. pore pressure prediction, fracture pressure gradient determination, casing setting depth, mud's rheological properties, hydraulics, bit selection and cementing program and service have to be highlighted more wisely when drilling into HPHT location (Shadravan and Amani, 2012). The difficulty of HPHT wells operation demands the use of specialized materials and front-line technologies to ensure efficient and safe operations.

The successful exploitation of HPHT wells is critical for meeting the growing global energy demands and has become a focus area for innovation in the oil and gas industry. "To control associated drilling problems in HPHT wells, it is important to design and formulate mud systems for any detailed drilling program, ensuring efficiency, safety, and environmental protection. HPHT are by far the most dominant problem impacting drilling fluids by damaging fluid properties such as decreasing viscosity, which will affect its ability to transport cuttings to the surface and maintain wellbore stability and decreasing drilling rate (Hansen et al., 2006). Additionally, the high pressure can affect the drilling fluid's density, which is essential for controlling the well's pressure. Therefore, particular mud systems are needed for HPHT wells, such as synthetic-based muds which are often used in these circumstances or conditions as they offer better performance in terms of minimizing differential sticking and barite sag problems, which are dominant in HPHT environments (Evans, 2003; Teodoriu et al., 2012).

Cementing in HPHT wells also faces major challenges. The main objective of cementing is to ensure casing strings are totally secure and isolate the different formations to prevent fluid movement. High temperatures can impact the hydration process of the cement, in turn decreasing strength development and durability of the cement. Moreover, high pressure can contribute to the loss of wellbore integrity, leading to sustained casing pressure and contamination of the adjacent environment (Yousuf et al., 2021). Development of cement technologies for HPHT-specific cement slugs have improved thermal stability and can withstand the high pressures faced in these wells (Nelson and Guillot, 2006). However, monitoring and controlling the well's pressure are crucial to prevent blowouts, which can have catastrophic consequences (Shadravan et al., 2014).

Drilling and exploration in the petroleum industry in HPHT oil wells require attentive planning, advanced technology, and special materials to overcome the major challenges exhibited by these high-pressure, high-temperature environments. For instance, (Tchagop and Oyelami, 2022) highlight that energy industry is constantly designing and developing equipment and operational workflows capable of operating in these HPHT conditions. Additionally, (Abdelhafiz et al., 2021) provide an extensive overview of thermal modelling techniques that are crucial for predicting temperature distributions within the wellbore, thus ensuring operational safety and efficiency. So, continuous research and development in this field are important to enhance safety and efficiency in HPHT oil and gas wells.

1.2. Background on Taylor-Couette flow

The Taylor-Couette flow, in which fluid is confined between two concentric cylinders that rotate independently, serves as a classic setup for the study of turbulence characteristics. The TC flow exhibits a wide array of intricate and fascinating patterns, influenced by the speed and direction of the cylinders' rotation (Gils, 2011). The flow within Taylor-Couette systems can vary from stable, laminar flow to complex, turbulent patterns. The transition to turbulence and the formation of Taylor vortices beyond a critical Taylor number are pivotal in fluid dynamics research. Taylor-Couette flow is not just of academic interest; its applications span across engineering, geophysics, astrophysics, and material science. The role of this flow in various industrial and scientific settings is highlighted in (Gils et al., 2013). TC system has been

thoroughly examined in terms of its roles in both linear and nonlinear hydrodynamic stability and its contributions to the development of turbulence models (Gils, 2011).

In the context of Taylor-Couette flow, which involves fluid motion between two rotating cylinders, the Generalized Reynolds Number is indispensable. It refines the classical Reynolds Number concept by integrating the non-linear rheological properties of non-Newtonian fluids, like shear-thinning or shear-thickening behaviours (Nielsen, 1978). This enhancement leads to more precise and relevant evaluations of non-Newtonian fluid dynamics. Numerous fluids in industry exhibit viscosity that is nonuniform based on numerous factors such as shear rate, shear history, and fluid viscoelasticity. These fluids are called non-Newtonian fluids (Singh et al., 2018).

2. Research methodology

2.1. The Taylor-Couette concept

At the core of TCS analyses are Navier-Stokes Equations applied within the cylindrical coordinate system specific to Taylor-Couette flow. These equations explain how a fluid's velocity field develops over time due to external forces acting upon it. The Navier-Stokes equations can be expressed in several forms, they have been discussed in paper (Rashidi et al., 2020). Boundary conditions in Taylor-Couette flow are defined by the angular velocities of the inner (Ω_1) and outer (Ω_2) cylinders (Fardin, 2014). Dimensionless numbers, such as the Reynolds number (Re) and the Taylor number (Ta), are crucial in understanding Taylor-Couette flow. The Reynolds number indicates the ratio of inertial to viscous forces, while the Taylor number, specific to this flow type, signifies flow instability based on rotation speeds and the gap between the cylinders (Ostilla-Mónico et al., 2016).

2.2. Experimental apparatus

The Taylor-Couette system viscometer (AUTCS) device is designed for studying and assessing fluid rheology in both laminar and turbulent flow regimes. The main objective here is to further enhance the first version of the AUTCS viscometer, initially developed in 2020 at Australian University of Kuwait (AU) by Rashidi et al. (2020). This involves increasing its speed from 1600 RPM to 3000 RPM, adding a speed selector for low and high-speed measurements, and incorporating a new heating film and controller, speed encoder, and power meters to facilitate data collection. The former model also suffered vibrations at high speeds. In the new AUTCS design, the structure of the device is improved. The upgraded AUTCS is detailed in Fig. 1, it retained the same

dimensions as the original AUTCS (Rashidi et al., 2021). However, it differed in materials, design, and exterior look which it made from aluminium and stainless steel in the outer cylinder and main body reduced rotation-induced vibration, consequently improved measurement accuracy. It holds an inner cylinder radius of 34 mm and an outer cylinder radius of 38 mm, with a 4 mm gap width between them.

The wet length of the cylinder is precisely 110 mm, and it can hold a volume of 100 ml in its wet annulus. The outer cylinder has a thickness of 3 mm, ensuring durability. For versatile operation, the electric DC motor supports a speed range of 0–3000 RPM at 24 V. The inner cylinder is crafted from aluminium for lightweight efficiency, while the outer cylinder is made of stainless steel for sturdiness. The device is equipped with top-bottom roller bearings that can handle up to 10,000 RPM, ensuring smooth operation. Furthermore, as illustrated in Fig. 2, it's outfitted with speed encoder with maximum rotation 5000 RPM, and film heater plater digital temperature controller to enhance its functionality and precision in various testing scenarios. Table 1 illustrates detailed specification of developed AUTCS (Rashidi et al., 2020).

2.3. Heating film and controller

The film heater plater incorporated into our device, controlled digitally to achieve precise temperature control. The design and fabrication of this film heater plater have been meticulously carried out to ensure it can reach and maintain the desired temperature levels. Detailed specifications for the heating film can be found in Table 2, and Fig. 3 provides a design sketch with dimensions.

In practical operation, the film plater is applied onto the outer wet cylinder, as depicted in Fig. 1, with temperature settings easily configured and adjusted using the digital temperature controller. This innovation holds promise for various applications where precise temperature control is essential, making it a valuable contribution to the field.

2.4. Calibration versus FANN viscometer

Calibration of devices is a critical process in scientific experimentation, ensuring that different instruments yield comparable results under identical conditions. This standardization is essential for the integrity of experimental data. For instance, when calibrating viscometers like the standard laboratory viscometer and the AUTCS, it's vital to use the same conditions for both devices to ensure consistency in measurements. This involves maintaining uniform test conditions such as temperature, pressure, and sample composition. This ensures that any differences in readings are due to the intrinsic characteristics of the devices rather than external variables. This practice of calibration under controlled conditions is widely acknowledged in scientific research and is emphasized in various studies and industry guidelines, as noted in sources like the American Society for Testing and Materials (ASTM) standards and ISO guidelines (eurolab); (ISO 3219, 1993). These references highlight the importance of consistent calibration practices across different types of equipment.

Two types of polymers, each at a concentration of 2 pounds per barrel (lb/bbl) in water-based mud were studied here. Specifically, we selected Flowzan and Xanthan Gum, well-recognized as viscosifying agents, to calibrate the AUTCS device. These polymers were subjected to tests at various temperatures: 79F, 104F, and 150F. Initially, the mud samples were analysed using a standard laboratory viscometer, before being further tested with the AUTCS.

The experiment began by preparing mud samples. One sample was mixed with Fluid 1 (Flowzan), as listed in Table 3, a polymer recognized for its high viscosity and stability at various temperatures. The other sample contained Fluid 2 (Xanthan Gum), noted in Table 4, which is valued for its superior pseudoplastic characteristics. For each polymer, a precise quantity of 2.77 g, equivalent to 2 pounds per barrel, was measured and then added to 500 mL of distilled water (Misbah et al., 2023). The mixture was agitated rigorously to ensure complete

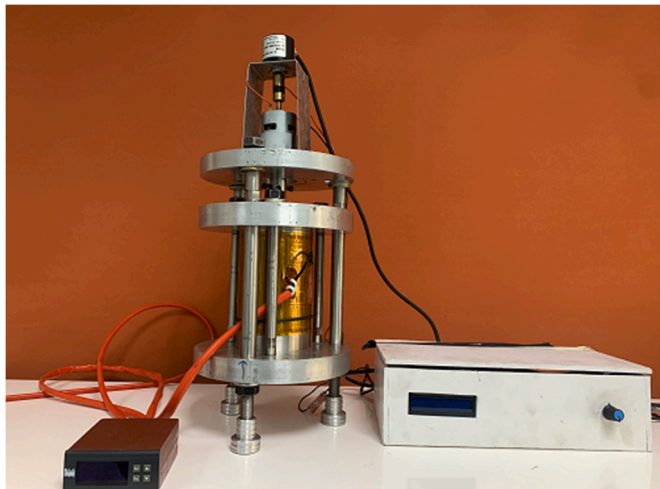


Fig. 1. The modified AUTCS viscometer.

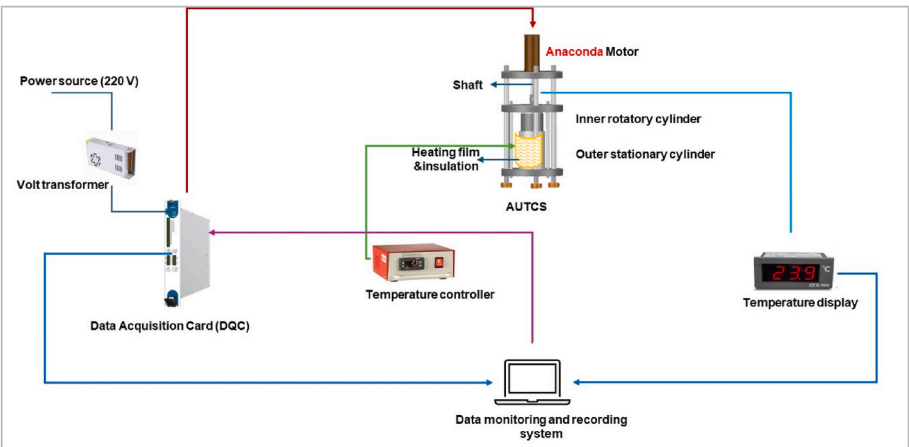


Fig. 2. Schematic of the AUTCS apparatus.

Table 1
Main specification and sizes of the AUTCS viscometer.

Parameters	values
Inner cylinder radius (R_i)	34 mm
Outer cylinder radius (R_o)	38 mm
Gap width (δ)	4 mm
Wet length of cylinder	110 mm
Wet annulus volume	100 ml
Thickness of outer cylinder	3 mm
Electric DC motor speed (12 v)	0–4500 RPM
Encoder speed	5000 RPM
Material of inner cylinder	Aluminium
Material of outer cylinder	Stainless steel
Thermal jacket with controller	1–350 F

Table 2
Technical specification of heating film.

Item description	
Material	Polyamide heater (with 3M glue in backside)
Film heater plater size	273*110 mm
Voltage	220V
Power	300–500W
wires	1000 mm x0.5

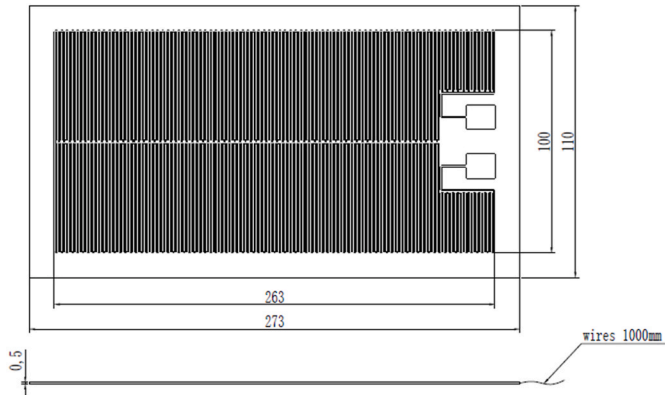


Fig. 3. Heating film's sketch with dimensions.

dissolution and uniformity, creating a homogenous suspension ideal for testing.

The calibration process involved subjecting these polymer solutions to a series of tests using a standard laboratory viscometer, (Misbah et al.,

Table 3
Fluid type 1.

Component	function	Concentration lb/bbl	Concentration grams
Distilled water	Base fluid	362 lb/bbl	500
Flowzan	Viscosifier	2 lb/bbl	2.77

Table 4
Fluid type 2.

Component	function	Concentration lb/bbl	Concentration grams
Distilled water	Base fluid	362 lb/bbl	500
Xanthan	Viscosifier	2 lb/bbl	2.77

2023). Measurements were taken at three critical temperatures—79F, 104F, and 150F—to capture the viscosity profile of the polymers across a spectrum of operational scenarios. This step was crucial to establish a baseline for subsequent comparative analysis.

Parallely, the Taylor-Couette viscometer (AUTCS) as shown in Fig. 1, an apparatus designed to measure fluid viscosity through the differential rotation of concentric cylinders, was calibrated. Initially, the AUTCS was operated devoid of any mud to fine-tune the speed settings, during which electrical parameters such as voltage and current were meticulously recorded at each speed increment. These readings were instrumental in calculating the mechanical power exerted by the air and intrinsic frictions, a factor critical to the calibration of the device.

Once the dry run was completed, the prepared mud samples were introduced into the AUTCS. The device was carefully adjusted to maintain a constant speed, ensuring that the testing temperature was held steady at 79F, 104F, or 150F. Observations continued as voltage and current data were captured at each speed level, enabling the calculation of mechanical power attributable to both the air and the fluid at room temperature. Consistency charts, the relationship between shear stress and viscosity versus angular velocity was plotted for both the FANN and the AUTCS devices. This graphical representation was the linchpin of the study, providing a visual confirmation that both devices exhibited analogous trends across the tested temperatures, thereby affirming the reliability and accuracy of the newly calibrated AUTCS against the established lab viscometer benchmarks.

3. Results and discussion

3.1. Analysis of AUTCS power

Upgrading and calibrating the Taylor-Couette High-Speed Viscometer is of paramount importance to improve its overall performance and

precision when studying mud properties, particularly in high-temperature and high-pressure drilling fluids/muds.

The AUTCS relies on power consumption measurements to analyse rheological properties. Initially, the device underwent testing to evaluate the power loss due to mechanical friction. Subsequently, the upgraded AUTCS was filled with polymer water-based mud (WBM), and its power usage was recorded. This process involved maintaining a stable state at each rotational speed. It's worth noting that unlike stepper motors, the speed controller of the DC motor in the Taylor-Couette system viscometer (AUTCS) does not allow for the establishment of a fixed speed value. Therefore, we used the best fit, to the raw data given in Table 5, to obtain power values at precise rotational speed of AUTCS. The AUTCS was utilized in conjunction with a standard viscometer to assess and calibrate the device while examining the characteristics of two different types of polymer water-based muds, namely Flow Zan and Xanthan, across a range of temperatures, specifically 79 F, 104 F, and 150 F. This testing aimed to both fine-tune the device's performance and gain insights into the properties of the muds under investigation.

The comprehensive power assessment for the evaluation of AUTCS using water-based polymer muds, both with and without polymer additives, encompasses two primary components: fluid power and air power. AUTCS's mechanical power (denoted as W) exhibits a direct proportionality to its angular velocity (measured in rad/s) when considering air, as elucidated in Table 6. In the case of the polymer-based muds, Xanthan and FlowZan, their fluid power across a range of tested temperatures is captured through polynomial equations relating rotational speed (rad/s). Specifically, for FlowZan, Table 6 outline the power flow at temperatures of 79F, 104F, and 150F, respectively. A similar function for Xanthan, shown in Table 4, portraying its fluid power at different temperatures of 79F, 104F, and 150F, respectively. These equations establish the fundamental connection between power and angular speed for air, along with the fluid power characteristics of Xanthan and FlowZan at varying temperatures.

3.2. Shear stress

Fluid torque, T , is obtained by diving the power correlation, P , given in Table 4 by the rotational speed, Ω , in the AUTCS as follows:

$$T = \frac{P}{\Omega} \quad (1)$$

For non-Newtonian and turbulent flow condition, the shear stress, τ , with a calibration factor, β , was determined as follows (Misbah et al., 2023):

$$\tau = \beta \frac{T}{2\pi R_i^2 L} \quad (2)$$

In eqn. (2), R_i is the inner cylinder radius and L is the length of inner cylinder. Shear rate, $\dot{\gamma}$, is obtained as follows (Misbah et al., 2023):

Table 5
Power values at various rotational speeds of AUTCS.

Ω (rpm)	Ω (rad/s)	I (Amp)	Power(W)
244	25.55	1.44	3.15
367	38.43	2.09	6.75
520	54.45	2.08	8.03
709	74.25	2.24	10.62
989	103.57	2.5	13.80
1372	143.68	2.8	19.12
1731	181.27	2.97	22.72
2000	209.44	3.07	26.77
2400	251.33	3.21	31.27
2747	287.67	3.28	34.11
3117	326.41	3.55	41.18

Table 6

Power correlations from measurements by AUTCS.

Power measurement (W)	Power Equation Fit ^a	R ² Accuracy
Mechanical power	$P = 0.1255\Omega$	0.9978
Flowzan at 79F	$P = 0.0002\Omega^2 + 0.1817\Omega$	0.9667
Flowzan at 104F	$P = 0.0003\Omega^2 + 0.1567\Omega$	0.9793
Flowzan at 150F	$P = 0.0003\Omega^2 + 0.1731\Omega$	0.9877
Xanthan at 79F	$P = 0.0008\Omega^2 + 0.5356\Omega$	0.9895
Xanthan at 104F	$P = 0.001\Omega^2 + 0.2127\Omega$	0.9989
Xanthan at 150F	$P = 0.0003\Omega^2 + 0.2341\Omega$	0.985

^a Ω the rotational speed is with the unit of rad/s.

$$\dot{\gamma} = \frac{2\Omega R_o^2}{R_o^2 - R_i^2} \quad (3)$$

In eqn. (3), R_o is the outer cylinder radius.

Figs 4a and 4b display the consistency charts of two distinct polymers, Xanthan and Flowzan, respectively, when shear stress is assessed across various shear rates at different temperatures are 79F, 104F, and 150F. These experiments employed FANN and AUTCS viscometers to ensure comprehensive coverage and validation of the rheological properties.

Both polymers exhibit non-Newtonian, shear-thinning behavior, characterized by a decrease in viscosity with increasing shear rate, as demonstrated by the power-law fit to the data. This behavior is consistently observed across all tested temperatures, as indicated by the high coefficients of determination (R^2) associated with the power-law model fits.

For Xanthan polymer Fig. 4b, the model equations and R^2 values indicate a more pronounced shear-thinning behavior at lower temperatures, with the highest viscosity observed at 79F ($y = 9.0058x^{0.1556}$, $R^2 = 0.993$). As the temperature increases, the viscosity decreases, which is reflected in the flattening of the curves and a decrease in the power-law exponent.

Conversely, Flow Zan polymer Fig. 4a demonstrates a lesser sensitivity to temperature changes, yet still exhibits a clear shear-thinning profile. The curve at 79F ($y = 6.4127x^{0.1058}$, $R^2 = 0.9934$) suggests a lower initial viscosity than Xanthan at the same temperature, and a more gradual decrease in viscosity with increasing temperature.

The differences in the rheological responses of the two polymers at equivalent temperatures are indicative of their unique molecular structures and interactions. While both polymers exhibit typical shear-thinning behavior, Xanthan polymer shows a higher sensitivity to temperature changes than Flowzan polymer.

3.3. The apparent viscosity

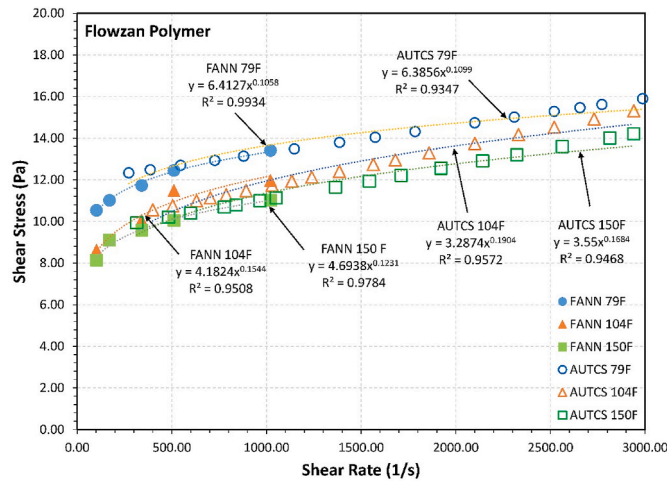
The apparent viscosity for non-Newtonian fluids was obtained in the AUTCS as follows (Misbah et al., 2022):

$$\eta = \frac{\tau}{\dot{\gamma}} \quad (4)$$

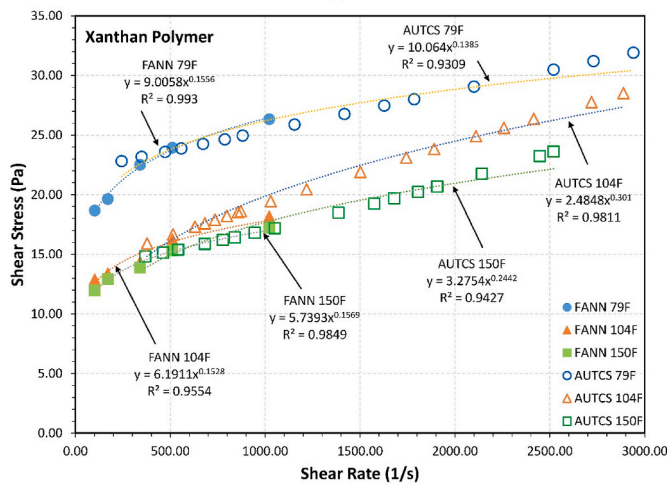
Figs 5a and 5b present a comprehensive analysis of the viscosity of Xanthan and Flowzan polymers, respectively, focusing on their response to varying shear rates at different temperatures as shown in the Fig. s.

Xanthan Polymer Fig. 5b reveals a pronounced shear-thinning effect. The viscosity significantly decreases with increasing shear rate, especially noticeable at high shear rates. This is quantitatively expressed by the power-law model, with the equation at 79F being $y = 9005.8x^{-0.844}$ and an R^2 of 0.9995, demonstrating a near-perfect correlation. The trend is consistent at elevated temperatures, albeit with a slightly reduced sensitivity to shear rate changes as reflected by the power-law exponents.

Flowzan Polymer Fig. 5a similarly exhibits a shear-thinning profile, with the decline in viscosity becoming less steep at higher shear rates.



(a) Flowzan



(b) Xanthan

Fig. 4. Consistency charts for muds at various temperatures.

The relationship between viscosity and shear rate at 79F is described by $y = 6412.7x^{-0.894}$, which holds an R^2 of 0.9999, indicating an exceptional fit to the model even at the upper end of the shear rate spectrum.

When comparing the behaviors at high shear rates, both polymers demonstrate a leveling off viscosity reduction, a typical behavior of shear-thinning fluids where the viscosity reaches a plateau at high shear rates, suggesting a limit to the decrease in viscosity regardless of further increases in shear rate. Both Xanthan and Flowzan polymers exhibit desirable characteristics that enable their use in scenarios where fluids are subjected to high shear stress, ensuring stable fluid properties under such conditions.

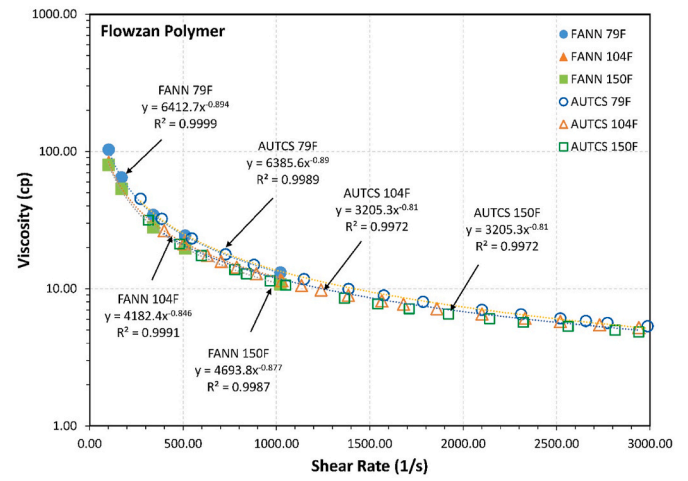
3.4. Darcy friction factor

The Darcy friction factor, f , for non-Newtonian fluids in the AUTCS was obtained as follows (Misbah et al., 2022):

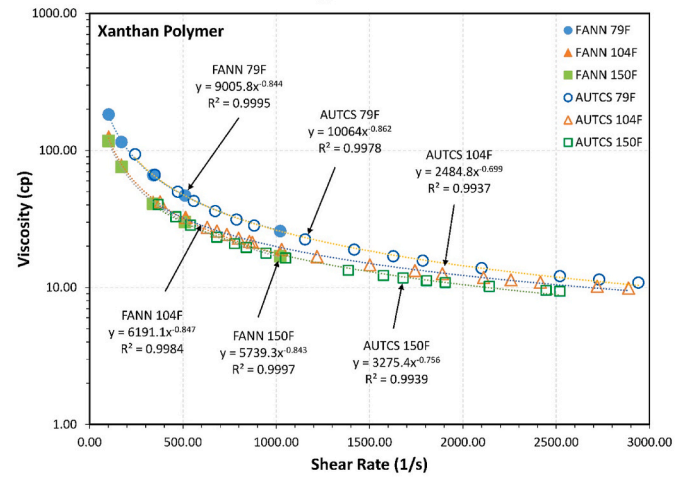
$$f = \frac{8\tau}{\rho \bar{u}^2} \quad (5)$$

In eq. (5), ρ is density of the mud and $\bar{u}$ is the average velocity obtained by integration of the flow velocity in the gap of AUTCS device (see Misbah et al., 2023).

According to the experimental data, it was evident that the measurement consistency of AUTSC with the Standard lab viscometer was



(a) Flowzan



(b) Xanthan

Fig. 5. Viscosity charts for muds at various temperatures.

observed. Furthermore, it was noted that the mud polymer's performance was influenced by both high temperatures and high speeds, resulting in distinct alterations in its behaviour.

Fig. 6a and b presents the friction factor of Flowzan and Xanthan polymer solutions, respectively, as a function of shear rate across different temperatures: 79F, 104F, and 150F. For both polymers, three distinct temperature-dependent trends are evident, each following a power-law relationship (Herschel-Bulkley model) as indicated by the best-fit lines with their corresponding equations: $y = ax^b$, where a and b are temperature-specific constants. The high R^2 values (>0.9987) across all temperature conditions for both polymers suggest that the power-law model robustly captures the shear-thinning behaviour. The slight variation in the exponent b across temperatures indicates a change in the degree of shear-thinning with temperature. The analysis provides a clear depiction of the flow characteristics of Flowzan and Xanthan polymers, highlighting their reduced flow resistance at higher shear rates and temperatures.

3.5. Summary of results

Table 7 compiles the rheological behaviors of two distinct fluid types, Flowzan and Xanthan, across a range of temperatures: 79F, 104F, and 150F. It includes specific equations that describe the relationship between the shear rate and each of three properties: the friction factor, shear stress, and viscosity. These properties are essential for

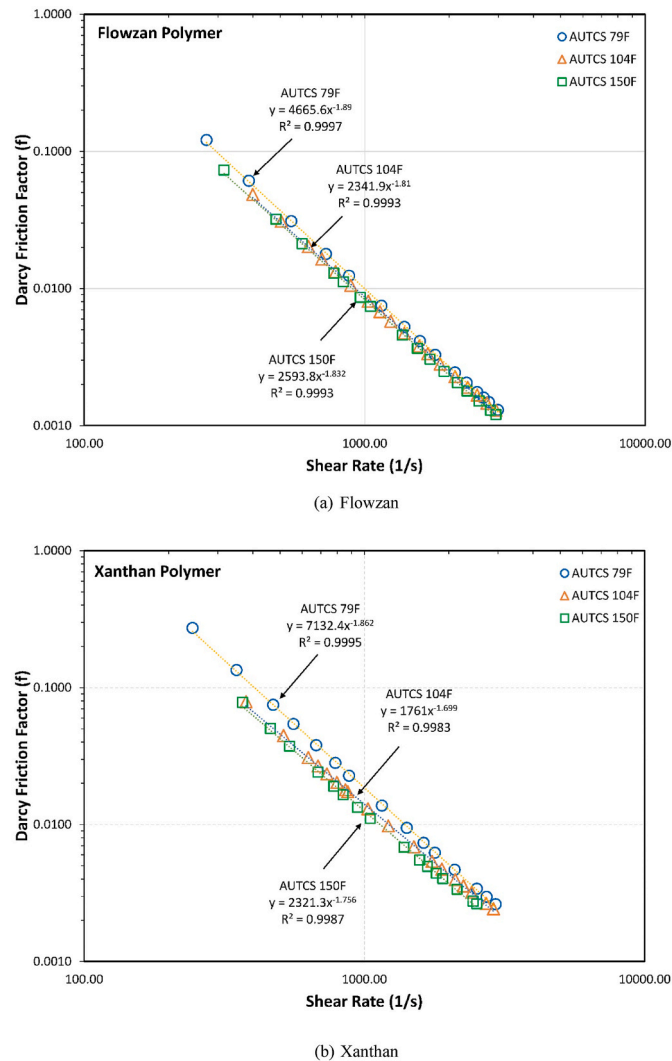


Fig. 6. Friction factor for muds at various temperatures.

understanding the flow behavior of the fluids under different conditions. Accompanying these equations are R^2 values, which are statistical measures of how closely the data fits the regression model, with a value closer to 1 indicating a better fit.

In the context of the table, 'x' corresponds to the shear rate, measured in inverse seconds (1/s), while 'y' varies depending on the property being described: it is the dimensionless Darcy Friction Factor for the friction factor, measured in Pascals for shear stress, and in centipoise for viscosity. The equations follow the power law form $y = ax^b$, where 'y' is the dependent variable that changes in response to 'x', the independent variable, and 'a' and 'b' are constants derived from fitting the model to the experimental data. The precision of these models, as indicated by the R^2 values, demonstrates the reliability of the equations in predicting the fluid behaviors at the specified temperatures.

4. Conclusions

The comprehensive analysis conducted on the Taylor-Couette High-Speed Viscometer post-upgrade demonstrates significant enhancements in measuring the rheological properties of drilling fluids under high-temperature and high-pressure conditions. Our findings from the AUTCS power consumption methodology indicate the following:

- **Precision and Calibration:** The precise calibration against standard viscometers has confirmed the accuracy of the AUTCS in evaluating

Table 7

Rheological correlations introduced for Flowzan and Xanthan.

Fluid type	Rheological properties	79 F	104 F	150 F
Flowzan	Friction factor	$Y = 4665.6x^{-1.89}$ $R^2 = 0.9997$	$Y = 2341.9x^{-1.81}$ $R^2 = 0.9993$	$Y = 2593.8x^{-1.832}$ $R^2 = 0.9993$
	Shear Stress (Pa)	$Y = 6.3856.6x^{0.1099}$ $R^2 = 0.9347; 0.9934$	$Y = 3.2874.6x^{0.1904}$ $R^2 = 0.9572; 0.9508$	$Y = 3.55x^{0.1684}$ $R^2 = 0.9468; 0.9784$
	Viscosity (cp)	$Y = 6385.6x^{-0.89}$ $R^2 = 0.9989; 0.9999$	$Y = 3205.3x^{-0.81}$ $R^2 = 0.9972; 0.9991$	$Y = 3205.3x^{-0.81}$ $R^2 = 0.9972; 0.9987$
		$Y^* = 6.4127x^{0.1058}$	$Y^* = 4.1824x^{0.1544}$	$Y^* = 4.6938x^{0.1231}$
Xanthan	Friction factor	$Y = 7132.4x^{-1.862}$ $R^2 = 0.9995$	$Y = 1761x^{-1.699}$ $R^2 = 0.9983$	$Y = 2321.3x^{-1.756}$ $R^2 = 0.9987$
	Shear Stress (Pa)	$Y = 10.064x^{0.1385}$ $R^2 = 0.9309; 0.993$	$Y = 2.4848x^{0.301}$ $R^2 = 0.9811; 0.9554$	$Y = 3.2754x^{0.2442}$ $R^2 = 0.9427; 0.9849$
	Viscosity (cp)	$Y = 10064x^{-0.862}$ $R^2 = 0.9978; 0.9995$	$Y = 2484.8x^{-0.699}$ $R^2 = 0.9937; 0.9984$	$Y = 3275.4x^{-0.756}$ $R^2 = 0.9939; 9997$
		$Y^* = 9.0058x^{0.1556}$	$Y^* = 6.1911x^{0.1528}$	$Y^* = 5.7393x^{0.1569}$

* Y value corresponds to AUTCS and Y^* to FANN viscometer devices.

polymer water-based muds, specifically Flowzan and Xanthan, across temperatures of 79F, 104F, and 150F.

- **Power Consumption Relationships:** The AUTCS showcased a direct proportionality of mechanical power to angular velocity in air and a polynomial relationship for fluid power with the muds, solidifying the device's utility for precise rheological analyses. In assessing the rheological properties, the following points were highlighted:
- **Darcy Friction Factor:** Both Flowzan and Xanthan polymers demonstrated a temperature-dependent shear-thinning behavior, following the Herschel-Bulkley model with high R^2 values, signifying a strong fit. This behavior suggests a decrease in flow resistance at increased shear rates and temperatures.
- **Shear Stress Behavior:** The polymers exhibited non-Newtonian, shear-thinning behavior across all temperatures, with Xanthan showing higher sensitivity to temperature changes compared to Flowzan. This was consistently reflected in the power-law model fits with high R^2 values.
- **Viscosity Trends:** A pronounced shear-thinning effect was observed for both polymers, with viscosity significantly reducing at higher shear rates. The power-law model equations provided a near-perfect fit, demonstrating the polymers' stability under shear stress.

The differences in molecular structure and interaction between the two polymers were evident, influencing their rheological responses at equivalent temperatures and shear rates. The study presents a robust set of data, confirming the suitability of the upgraded AUTCS for detailed rheological studies and its application in the formulation of drilling fluids capable of withstanding the demanding conditions of high-temperature oil wells. The consistency and accuracy of the results obtained from the AUTCS provide a valuable benchmark for future research and application in the field of drilling fluid engineering.

CRediT authorship contribution statement

Biltayib Misbah: Writing – original draft, Methodology. **Rida Elgaddafi:** Writing – review & editing. **Rana N. Malhas:** Supervision, Conceptualization. **Suad Al Radhwan:** Data curation. **Asama Hussain:** Formal analysis. **Ali Hersi:** Validation, Investigation.

Declaration of interest statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

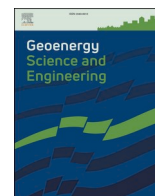
Data will be made available on request.

Acknowledgements

We express our gratitude to the Petroleum Department and the Research Centre at Australian University in Kuwait for their support in our research endeavors. Their contributions were essential to the advancement of this study, for which we are deeply thankful.

References

- Abdelhafiz, M.M., Hegele, L.A., Oppelt, J.F., 2021. Temperature modeling for wellbore circulation and shut-in with application in vertical geothermal wells. *J. Petrol. Sci. Eng.* 204, 108660 <https://doi.org/10.1016/j.petrol.2021.108660>.
- Al-Rubaii, M., et al., 2023. A novel automated model for evaluation of the efficiency of hole cleaning conditions during drilling operations. *Appl. Sci.* 13 (11), 6464. <https://doi.org/10.3390/app13116464>, 2023.
- Biltayib, B.M., Rashidi, M., Balhasan, S., Alothman, R., Kabuli, M.S., 2018. Experimental analysis on rheological and fluid loss control of water-based mud using new additives. *J. Petrol. Gas Eng.* 9, 23–31.
- Davoodi, S., Al-Shargabi, M., Wood, D.A., Rukavishnikov, V.S., Minaev, K.M., 2023. Thermally stable and salt-resistant synthetic polymers as drilling fluid additives for deployment in harsh sub-surface conditions: a review. *J. Mol. Liq.* 371, 121117 <https://doi.org/10.1016/j.molliq.2022.121117>.
- Drilling Fluids Processing Handbook, 2005. Elsevier. <https://doi.org/10.1016/B978-0-7506-7775-2.X5000-8>.
- eurolab, n.d. Determination of Viscosity (ASTM D 445) [WWW Document]. URL <https://www.eurolab.net/en> (accessed 12.27.23).
- Evans, B., 2003. Fluid loss control – improvement for HTHP wells. Presented at the SPE Production and Operations Symposium. OnePetro. <https://doi.org/10.2118/80946-MS>.
- Ezell, R., Harrison, D.J., 2008. Design of improved high-density, thermally-stable drill-in fluid for HTHP applications. Presented at the SPE Annual Technical Conference and Exhibition. OnePetro. <https://doi.org/10.2118/115537-MS>.
- Fardin, Marc A., et al., 2014. Flow instabilities in large amplitude oscillatory shear: a cautionary tale. In: , 53. Springer link, pp. 885–898. Published: 18 November.
- Galindo, K.A., Zha, W., Zhou, H., Deville, J.P., 2015. High temperature, high performance water-based drilling fluid for extreme high temperature wells. Presented at the SPE International Symposium on Oilfield Chemistry. OnePetro. <https://doi.org/10.2118/173773-MS>.
- Gils, D.P.M. van, 2011. Highly Turbulent Taylor-Couette Turbulence (PhD). University of Twente, Enschede, The Netherlands. <https://doi.org/10.3990/1.9789036532723>.
- Gils, D.P.M. van, Guzman, D.N., Sun, C., Lohse, D., 2013. The importance of bubble deformability for strong drag reduction in bubbly turbulent Taylor–Couette flow. *J. Fluid Mech.* 722, 317–347. <https://doi.org/10.1017/jfm.2013.96>.
- Hansen, S.A., Breivik, D.H., Gjonnes, M., Svanes, K., Vujovic, M., Sveta, P.E., Sørheim, O. I., 2006. Drilling fluids in an HP/HT reservoir: experiences with three different systems on the kristin field development. Presented at the SPE Annual Technical Conference and Exhibition, OnePetro. <https://doi.org/10.2118/103336-MS>.
- ISO 3219, 1993. (en), Plastics — Polymers/resins in the liquid state or as emulsions or dispersions — Determination of viscosity using a rotational viscometer with defined shear rate [WWW Document]. URL. <https://www.iso.org/obp/ui/#iso:std:iso:3219:ed-2:v1:en> (accessed 12.27.23).
- Lake, Larry W., 2019. *Petrol. Eng. Handb.* 1, 68–85.
- Misbah, B., Sedaghat, A., Balhasan, S., Elgaddafi, R., Malayer, M.A., Malhas, R.N., Omar, M., Benomran, M., 2023. Enhancing thermal stability and filtration control for water-based drilling fluid using viscosifier polymers and potassium chloride additives. *Geoenergy Science and Engineering* 230, 212235. <https://doi.org/10.1016/j.geoen.2023.212235>.
- Misbah, Biltayib, Sedaghat, Ahmad, Rashidi, Masoud, Sabati, Mohammad, Koshy, Vaidyan, Ali, Naser, 2022. Friction reduction of Al₂O₃, SiO₂, and TiO₂ nanoparticles added to non-Newtonian water based mud in a rotating medium. *J. Petrol. Sci.*
- Nelson, E.B., Guillot, D., 2006. *Well Cementing*. Schlumberger.
- Nielsen, L.E., 1978. Predicting the properties of mixtures : mixture rules in science and engineering. 2016. Considerations of Well Cementing Materials in High-Pressure, High-Temperature Conditions (RESEARCH NOTE). *International Journal of Engineering* 29, 1214–1218. M. Dekker, New York Nikolaev, N., Tabatabaee Moradi, S.S.
- Ostilla-Mónico, Zhu, Xiaojue, Rodolfo, Verzicco, Roberto, Lohse, Detlef, 2016. Direct numerical simulation of Taylor–Couette flow with grooved walls: torque scaling and flow structure. Published online by Cambridge University Press.
- Phi, T., Elgaddafi, R., Al Ramadan, M., Ahmed, R., Teodoru, C., 2019. Well integrity issues: extreme high-pressure high-temperature wells and geothermal wells a review. Presented at the SPE Thermal Well Integrity and Design Symposium. OnePetro. <https://doi.org/10.2118/198687-MS>.
- Rashidi, M., Sedaghat, A., Misbah, B., Sabati, M., Vaidyan, K., 2020. Developing a Taylor–Couette stand-alone viscometer for testing drilling fluids with turbulent nano fluid flow and testing stability of different shale materials. Kuwait Foundation for the Advancement of Science (KFAS) 2021, 14. Grant No. PR18–15EP-01. (Accessed August 2020). Article ID 1344776.
- Rashidi, Masoud, Sedaghat, Ahmad, Misbah, Biltayib, Sabati, Mohammad, Vaidyan, Koshy, Mostafaiepour, Ali, Hosseini Dehshiri, Seyyed Shahabaddin, Almutairi, Khalid, Issakhov, Alibek, 2021. Introducing a rheology model for non-newtonian drilling fluids Hindawi. *Geofluids*.
- Salim and Amani, 2013. Special considerations in cementing high pressure high temperature well. In: *International Journal of Engineering and Applied Sciences*, 1. No.4 Texas A&M University, Qatar.
- Sayindla, S., Lund, B., Ytrehus, J.D., Saasen, A., 2019. CFD modeling of hydraulic behavior of oil- and water-based drilling fluids in laminar flow. *SPE Drill. Complet.* 34, 207–215. <https://doi.org/10.2118/184660-PA>.
- Shadravan, A., Amani, M., 2012. Hpht 101: what every engineer or geoscientist should know about high pressure HighTemperature wells. <https://doi.org/10.2118/163376-MS>.
- Shadravan, A., Schubert, J., Amani, M., Teodoru, C., 2014. HPHT cement sheath integrity evaluation method for unconventional wells. In: *SPE International Conference and Exhibition on Health, Safety, Environment, and Sustainability? SPE. D021S044R004*.
- Singh, J., Rudman, M., Blackburn, H.M., 2018. Reynolds number effects in pipe flow turbulence of generalized Newtonian fluids. *Phys. Rev. Fluids* 3, 094607. <https://doi.org/10.1103/PhysRevFluids.3.094607>.
- Tchagop, A., Oyelami, O., 2022. Managing the high-temperature drilling challenges of deepwater HP/HT wells: a gulf of Mexico case study. Presented at the SPE Annual Technical Conference and Exhibition, OnePetro. <https://doi.org/10.2118/210122-MS>.
- Teodoru, C., Bello, O., 2021. An outlook of drilling technologies and innovations: present status and future trends. *Energies* 14, 4499. <https://doi.org/10.3390/en1454499>.
- Teodoru, C., Kosinowski, C., Amani, M., Schubert, J., Shadravan, A., 2012. *WELLBORE INTEGRITY AND CEMENT FAILURE AT HPHT CONDITIONS*, 2.
- Wang, F., Tan, X., Wang, R., Sun, M., Wang, L., Liu, J., 2012. High temperature and high pressure rheological properties of high-density water-based drilling fluids for deep wells. *Petrol. Sci.* 9, 354–362. <https://doi.org/10.1007/s12182-012-0219-4>.
- Yousuf, N., Olaiyiwola, O., Guo, B., Liu, N., 2021. A comprehensive review on the loss of wellbore integrity due to cement failure and available remedial methods. *J. Petrol. Sci. Eng.* 207, 109123 <https://doi.org/10.1016/j.petrol.2021.109123>.



Sustainable conversion of petroleum sludge to methane: A study on anaerobic biodegradability in batch and continuous systems

Jean H. El Achkar^{*}, Rana Malhas, Faisal Albalool, Abdullah Alrabaie

Petroleum Engineering Department, College of Engineering, Australian University, West Mishref, Safat, 13015, Kuwait

ARTICLE INFO

Keywords:

Anaerobic digestion
Petroleum sludge
Methane production
Biodegradability
Kinetic modeling
Batch reactor
Continuous reactor

ABSTRACT

This study investigates the anaerobic digestion of petroleum sludge from Kuwait's oil and gas industry to promote bioenergy production and waste management. Experiments were conducted at 37 °C and 45 °C in batch reactors using local cow manure as inoculum, following a Total Solids (TS) ratio in the digesters of 3/1 (Inoculum/Substrate). The batch study included three experimental groups: inoculum alone, inoculum with oily sludge, and inoculum with desalter sludge, each tested in duplicate. The inoculum with the oily sludge group achieved the highest methane yield, producing 5.16 L by day 60 at 45 °C. This represents a 35% increase in methane production compared to the yield at 37 °C. The Modified Gompertz Model provided a robust fit to the experimental data, predicting methane yields of 69.8 NL/kg COD at 37 °C and 154.0 L/kg COD at 45 °C. The anaerobic biodegradability of oily sludge improved significantly under higher temperatures, with rates increasing from 19.9% at 37 °C to 44% at 45 °C. Continuous digestion experiments at 45 °C over 120 days, under an HRT of 30 days and an OLR of 2.5 Kg COD/m³/day, revealed stable methane production during the steady-state phase, peaking at 108 NL CH₄/kg COD/day. Energy estimation results indicated a theoretical thermal energy potential of 1071.83 kWh/day, with a net energy production of 850.88 kWh/day. The total thermal energy demand for the process was 220.95 kWh/day, underscoring the process's efficiency. This study offers valuable insights into optimizing anaerobic digestion for petroleum sludge, demonstrating substantial improvements in biomethane production and energy recovery. The findings provide a foundation for sustainable waste management strategies in the petroleum industry, contributing to net-zero emissions and carbon-neutral goals.

1. Introduction

The urgency of mitigating climate change effects and promoting sustainable development has become a global concern (Klenert et al., 2020). Climate change is primarily driven by nonrenewable fuels and the consequent greenhouse gas (GHG) emissions, which pose severe environmental and existential threats (Brauer and Khan, 2021). Improper disposal of industrial byproducts further exacerbates GHG emissions (Chen, 2018). Waste disposal contributes to 6% of global GHG emissions, while fossil fuels accounted for 93% of global CO₂ emissions in 2020 (Ritchie and Roser, 2020). Consequently, waste management is a critical focus for industrial sectors striving to meet the United Nations' Sustainable Development Goals (SDGs).

Innovative technologies that facilitate optimal waste management and energy recovery are essential for sustainable bio-economy development (El Achkar, 2022; Yaashikaa et al., 2020). The transition from

fossil fuels to renewable energy sources is imperative. Bioenergy recovery from solid waste (waste-to-energy) can enhance operational profitability, minimize environmental impacts, and reduce GHG emissions (Van et al., 2020).

The petroleum industry generates substantial amounts of Petroleum Sludge (PS) during oil exploration, production, refining, and effluent treatment (El Achkar et al., 2022; Jerez et al., 2021). PS consists of polycyclic aromatic hydrocarbons, benzene homologs, oil, grease, and various toxic metals and organic chemicals (Kankia et al., 2021). This hazardous composition makes PS cytogenic, mutagenic, and carcinogenic (Johnson and Affam, 2019). Improper disposal of PS can lead to environmental contamination and health hazards. Despite existing treatment technologies, the high production volume and potential dangers of PS necessitate effective and green treatment solutions.

Current PS treatment technologies include incineration, oxidation, stabilization, and biodegradation (Murungi and Sulaimon, 2022). Each

^{*} Corresponding author.

E-mail address: j.achkar@au.edu.kw (J.H. El Achkar).

<https://doi.org/10.1016/j.geoen.2025.213816>

Received 2 June 2024; Received in revised form 28 July 2024; Accepted 4 March 2025

Available online 5 March 2025

2949-8910/© 2025 Elsevier B.V. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

method has challenges, such as GHG emissions, toxic leachate infiltration, and heavy metal accumulation. Thermochemical and solidification treatments are extensively used to treat solid petroleum waste, although biological treatment is not well documented in the literature. One cause is a lack of "know-how" about the digestion of such effluent and its favorable biodegradation conditions (Kardena, 2015). Recycling PS into valuable products or processing it through environmentally friendly methods like composting or Anaerobic Digestion (AD) has become crucial (El Achkar, 2022).

AD is a biological process for managing organic waste and recovering bioenergy through microbial digestion without oxygen (Ampese et al., 2022; Zamri et al., 2021). This process produces biogas, primarily methane, which can be used for heat and electricity generation, reducing the reliance on fossil fuels (Hakawati et al., 2017). AD is considered one of the best environmentally friendly alternatives for organic waste management due to its reduced environmental footprint, high energy recovery potential, and biofertilizer production (El Achkar et al., 2018a, 2018d, 2020).

Although several studies have demonstrated the potential for biogas production from refinery wastewater, research on bioenergy production from PS through AD is limited (Haak et al., 2016; Paul Choudhury et al., 2022; Roy et al., 2016; Wang et al., 2016). Given the increasing demand for crude oil and the finite nature of fossil fuel reserves, it is crucial to explore sustainable energy sources. Converting PS into a green energy source through AD could optimize petroleum production, promote sustainable development, and mitigate environmental risks (El Achkar et al., 2022).

A study found that co-digesting 60% petroleum hydrocarbon waste with 40% wastewater treatment sludge at 35 °C in batch reactors maximized biogas production (Janajreh et al., 2020). Additionally, post-coagulation sludge from petroleum-produced water showed potential as a substrate for biogas generation when co-digested with cow manure (Ezemagu et al., 2020). A recent study examined the biochemical methane potential of buffalo dung mixed with PS in ratios of 1:1, 1.5:0.5, and 0.5:1.5. The highest methane production was obtained at a 1.5:0.5 ratio. The results suggest that this ratio is the most effective for enhancing methane production (Korai et al., 2024).

Given the gaps in the literature, this study explores the AD of PS for bioenergy production. Previous research has not thoroughly assessed methane production from PS in both batch and continuous reactors, evaluated the process at different temperatures, or tested various types of sludge. This study focuses on two types of PS samples selected from Kuwait's local oil and gas industry: oily sludge and desalter sludge. Oily sludge accumulates in storage tanks, separators, and other equipment where oil-water separation occurs. Desalter sludge is produced during the desalting process in refineries, where crude oil is treated to remove salts and impurities before further refining. Both types of sludge are generated in significant quantities during petroleum processes, although exact amounts vary with production levels. These two sludge types represent the primary categories of PS and often remain unvalorized, posing a significant waste management challenge. This study aims to enhance the understanding of AD for treating these prevalent forms of petroleum refinery waste, providing valuable insights for sustainable waste management in the industry. Consequently, the primary objectives of this study are (1) to assess the physical-biochemical characterization of the sludge samples (oily and desalter sludge) obtained from local industries in Kuwait, (2) to evaluate methane production from the samples using cow manure as inoculum at two different temperatures (37 °C and 45 °C), (3) to perform a kinetic study to understand the methane production dynamics, (4) to extrapolate the study to continuous reactors for better scalability, and (5) to conduct an energy estimation study for the AD process and Combined Heat and Power (CHP) system. This study provides novel insights into the AD of PS and its potential for bioenergy production, addressing gaps in the existing literature.

2. Materials and methods

2.1. Raw materials

Petroleum Sludge (PS) samples were obtained from Kuwait's local oil and gas industry. Two types of sludges were collected: 1) Oily Sludge deposited in tanks and 2) Desalter Sludge deposited in desalter units. Samples were transported and kept in the lab at ambient temperature until used. Before the AD tests, the inoculum (cow manure) was collected from a local dairy farm in Kuwait.

2.2. Analytical methods

According to APHA standard procedures, PS samples were examined for TS (American Public Health Association et al., 2005). The pH was monitored using a WTW pH meter model Multi 340i. In addition, the Chemical Oxygen Demand (COD), Total Phosphate P, and total Nitrogen N were also determined using UNI 10780. The Higher Heating Value (HHV) was estimated utilizing a Plain Jacket Bomb Calorimeter (model PARR 1341). A differential scanning calorimeter (Mettler Toledo DSC823) was used to determine the specific heat of PS. All analyses were performed in triplicate.

2.3. Biochemical methane potential (BMP) measurement

The Biochemical Methane Potential (BMP) tests were conducted using the Automatic Methane Potential Test System (AMPTS, Bioprocess Control, Sweden) (Fig. 1). This system is designed for online measurement of ultra-low biomethane flows generated from the AD of degradable wastes. The AMPTS II Light enables multiple anaerobic batch fermentation tests, accommodating up to six test vials. It facilitates BMP tests with integrated sampling, analysis, recording, and report generation.

2.3.1. Sample incubation

Small amounts of sample mixed with anaerobic inoculum were incubated at the desired temperature in up to six vials in the sample incubation unit. A slow-rotating agitator mixed the solution in each vial to ensure uniformity. The recurring biogas production was monitored to estimate the AD activity within each vial.

2.3.2. CO₂ absorption unit

To separate carbon dioxide (CO₂) from biogas, absorption using sodium hydroxide (NaOH) was employed. The NaOH reacts with CO₂ to form sodium carbonate (Na₂CO₃) and water, increasing the biogas's methane (CH₄) concentration. This method ensures a higher methane purity (up to 99%) by removing CO₂.

2.3.3. Gas volume measurement

The volume of methane gas produced after CO₂ absorption was measured using a multi-flow cell device. This device accurately measures the volume of methane passing through it, providing reliable data on methane production.

2.3.4. Temperature selection

The AD experiments were conducted at two different temperatures: 37 °C and 45 °C. While 37 °C is commonly used for mesophilic AD, 45 °C was selected due to its alignment with the average temperature during Kuwait's hot months. This intermediate temperature leverages the benefits of higher temperature digestion, such as enhanced hydrolysis and increased methane production, without the high energy costs of maintaining a thermophilic temperature of 55 °C. Operating at 45 °C minimizes the need for additional heating, reducing energy consumption and making the process more economical and environmentally friendly. This approach provides insights into the efficiency of AD under realistic local conditions, highlighting the potential for sustainable



Fig. 1. AMPTS II setup for batch experiments, including the sample incubation unit, CO₂ absorption unit, and gas volume measurement unit connected to a computer for live monitoring.

bioenergy production in similar climatic regions.

2.3.5. Inoculum preparation

Local cow manure was used as the inoculum due to its availability, cost-effectiveness, and established use in anaerobic digestion studies. Additionally, in the absence of industrial anaerobic digesters in Kuwait, cow manure is the best available source of anaerobic bacteria. It contains a diverse microbial community essential for facilitating the anaerobic digestion process. The manure underwent a pretreatment process where it was first sieved through a 300 µm sieve to remove large particles and then diluted with water to achieve a Total Solids (TS) rate of 5%. The COD level of the obtained inoculum was approximately 50 gO₂/kg. The methane production from the cow manure alone (used as a control) was measured separately and subtracted from the total methane production observed in the sludge groups. This approach allows the determination of the exact methane production from the sludge alone.

2.3.6. Digesters composition

The composition of the digesters used in the AMPTS experiments under 37 °C and 45 °C is detailed in Table 1. The weights of manure and sludge, along with their total solids' percentage and inoculum-to-sludge ratio, were carefully measured to ensure consistency across all experiments. The exact composition was maintained for experiments conducted at both temperature settings, 37 and 45 °C.

The study was designed with replicates to ensure the reliability and

robustness of the results. Each experimental group was tested using duplicate reactors. This approach was taken to account for potential variability and to provide more convincing and accurate results. Using replicates allows for verifying the consistency of the observed trends in methane production and biodegradability.

2.3.7. Biodegradability calculation

To evaluate the anaerobic biodegradability of the sludge, the highest volume of methane produced was used to calculate the biodegradability percentage. The following formula was applied:

$$\text{Biodegradability \%} = \frac{\text{Highest methane production of sludge (L)}}{\text{COD in sample (Kg)}} \times \frac{1 \text{ (Kg)}}{350 \text{ (L)}} \times 100 \quad (\text{Eq. 1})$$

In this formula, 350 represents the theoretical maximum methane yield of 350 NL CH₄/kg COD under standard temperature and pressure conditions (0 °C, 1013 hPa) (Buffiere et al., 2008).

2.4. Kinetics modeling

The kinetics of methane production in batch mode during the AD of PS were modeled using the Modified Gompertz Model. The Modified Gompertz Model is widely used in biogas production studies because it accurately describes the cumulative methane production curve in batch AD tests (Kunatsa and Xia, 2022). It accounts for the initial lag, exponential growth, and stationary phases of microbial activity, providing a comprehensive understanding of the digestion kinetics. Compared to the original Gompertz Model, the Modified Gompertz Model incorporates the maximum methane production rate (R), making it more suitable for predicting methane production. Moreover, the inclusion of the lag phase (λ) allows for better fitting of experimental data, especially in cases where there is a delay in microbial activity due to acclimatization or other factors (K et al., 2024).

The following equation represents the Modified Gompertz Model:

$$\text{BMP}_i = P \times \exp \left\{ - \exp \left[\left(\frac{R \times e}{P} \right) \times (\lambda - t) + 1 \right] \right\} \quad (\text{Eq. 2})$$

where.

- BMP_i is the biochemical potential of accumulated methane (L/kg_{COD}),

Table 1

Composition of digesters used in the AMPTS experiments, under 37 and 45 °C.

Digesters	Total Solids (TS) of the substrate (%)	Manure weight (g)	Inoculum/Sludge Ratio (weight of TS)	Sludge weight (g)	Final TS in each digester (%)
(1, 2) ^a Inoculum	5.0	1600	3/1	–	5.0
(3, 4) ^a Desalter Sludge	78.1	1600	3/1	34.1	6.52
(5, 6) ^a Oily Sludge	69.5	1600	3/1	38.4	6.51

^a Each experimental group consists of two samples to ensure the reliability of the results. Samples 1 and 2 are duplicates for the cow manure (inoculum) group, samples 3 and 4 for the cow manure and desalter sludge group, and samples 5 and 6 for the cow manure and oily sludge group.

- P is the maximum value of BMP recorded at the end of the test (L/kg_{COD}),
- R is the maximum methane production rate (L/kg_{COD}/day),
- λ is the lag phase time (days),
- t is the time (days),
- e is Euler's number (approximately 2.71828).

2.5. Methane production in continuous reactors

The system established for continuous methane production measurement includes three central components. The incubation unit comprised a thermostatic water bath housing 2 L digesters containing cow manure and oily PS (Fig. 2). The continuous reactor has two sealable tubes, one for extracting the digestate and the other for introducing the feed. Each digester was agitated daily to ensure optimal mixing (El Achkar, 2017).

The biogas generated was channeled through a connecting tube from the incubation unit to the CO₂ fixation unit, consisting of a 6 M NaOH solution to capture CO₂, with thymolphthalein, an acid-base pH indicator. Consequently, the methane generated was measured in the third unit using water displacement.

This experimental setup was subjected to a distinct temperature setting of 45 °C. The uniform oily sludge samples served as the feedstock for all trials. A daily routine of feeding and extraction was followed based on an HRT of 30 days and a final OLR set at 2.5 Kg COD/m³/day. The alkalinity and total volatile acidity (TVA) were also determined per the standardized procedure (El Achkar, 2017).

During the start-up period (0–28 days), the OLR was gradually increased to allow the microbial community to acclimatize to the oily sludge. The OLR was incremented from 0.5 Kg COD/m³/day (7 days) to 1.0 Kg COD/m³/day (7 days), then to 1.5 Kg COD/m³/day (7 days), 2.0 Kg COD/m³/day (7 days), and finally to 2.5 Kg COD/m³/day. After reaching this OLR, digesters underwent a 90-day operational period, equivalent to thrice the HRT, ensuring the system reached a stable state, marked by stable gas production (El Achkar et al., 2018b).

2.6. Energy estimation methodology

The energy estimation for the AD process and the Combined Heat and Power (CHP) system was performed using an adapted methodology from the literature (Szaja et al., 2021; Szaja and Montusiewicz, 2019). The analysis involves calculating the daily methane production, the theoretical thermal energy obtained from methane combustion, and the thermal energy required to heat the digester and cover heat losses. The equations used in the calculations and their meanings are detailed

below.

2.6.1. Methane production

The daily methane production (Q_{CH₄}) is calculated using the methane yield (Y_m) and the solids load (L).

$$Q_{CH_4} = Y_m \times L \quad (\text{Eq. 3})$$

where.

- Q_{CH₄} is the daily methane production (m³ CH₄/day).
- Y_m is the methane yield (m³ CH₄/kg COD).
- L is the total load of chemical oxygen demand (COD) in the feedstock (kg COD/day).

2.6.2. Thermal energy

The theoretical amount of thermal energy (Q_t) obtainable from the combustion of methane is given by:

$$Q_t = Q_{CH_4} \times Q_i \quad (\text{Eq. 4})$$

where.

- Q_t is the theoretical thermal energy (MJ/day).
- Q_i is the heating value of methane (35.8 MJ/m³ CH₄).

Thermal Energy Demand:

Two components are considered to determine the thermal energy demand: the energy required for heating the feedstock (Q₁) and the energy necessary to cover the heat loss through the digester walls (Q₂).

a Thermal Energy Required for Heating the Feedstock:

$$Q_1 = V_{os} \times (T - T_{feed}) \times C_{PS} \quad (\text{Eq. 5})$$

where.

- Q₁ is the thermal energy required for heating the feedstock (kJ/day).
- V_{os} is the feedstock flow rate (m³/day).
- T is the AD temperature (K).
- T_{feed} is the feedstock temperature (K).
- C_{PS} is the specific heat of PS (2950 kJ/m³ K).

bThermal Energy Required to Cover Heat Loss:

$$Q_2 = 24 \times (T - T_{air}) \times U \times F \quad (\text{Eq. 6})$$

where.

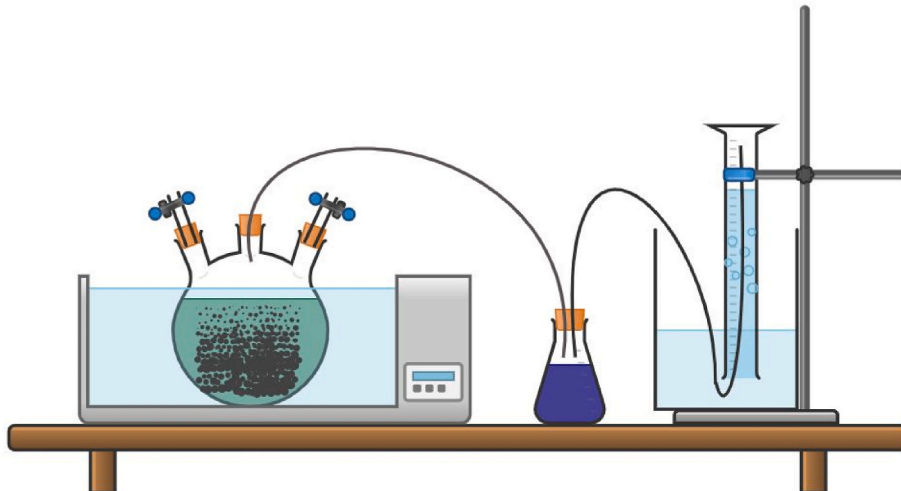


Fig. 2. Setup used for monitoring methane production in continuous mode.

- Q_2 is the thermal energy required to cover heat loss (kJ/day).
- T_{air} is the ambient temperature (K).
- U is the heat loss coefficient by permeation through the walls of the digester ($4.0 \text{ kJ/m}^2 \text{ h K}$).
- F is the surface area of the digester walls (m^2).
The surface area of the digester walls (F)

The surface area of the digester walls (F) is calculated using the following equation:

$$F = 3.17 \times D^2 \quad (\text{Eq. 7})$$

where,

- D is the diameter of the cylindrical part of the digester (m).

Total Thermal Energy Demand:

The total thermal energy demand (Q_c) is calculated by combining (Q_1) and (Q_2) with a margin factor of 1.1:

$$Q_c = 1.1 \times (Q_1 + Q_2) \quad (\text{Eq. 8})$$

2.6.3. Energy production

The daily energy production (E_d) is given by:

$$E_d = Q_{CH4} \times Q_i \quad (\text{Eq. 9})$$

Thermal and electrical efficiency.

The thermal and electrical efficiency of the CHP engine is considered using the following equations.

a Thermal Efficiency:

$$N_t = \left(\frac{Q_{CH4}}{24} \right) \times Q_i \times \eta_t \quad (\text{Eq. 10})$$

where,

- N_t is the thermal energy output (MJ/day).
- η_t is the thermal efficiency of the CHP engine (0.43).
- b Electrical Efficiency:

$$N_e = \left(\frac{Q_{CH4}}{24} \right) \times Q_i \times \eta_e \quad (\text{Eq. 11})$$

where,

- N_e is the electrical energy output (MJ/day).
- η_e is the electrical efficiency of the CHP engine (0.38).

2.6.4. Data used for calculations

Assumptions. for the calculations include a methane yield (Y_m) of $107.80 \text{ L CH}_4/\text{kg COD}$ (experimental result obtained from this study) and a total load (L) of 1000 kg COD/day . The temperatures were 45°C (318 K) for AD, 27.5°C (300.5 K) as the annual average air temperature in Kuwait, and 25°C (298 K) for the feedstock. The feedstock flow rate (Vos) was $10 \text{ m}^3/\text{day}$, and the digester (D) diameter was 5 m .

These data points were used to estimate energy and determine the feasibility and efficiency of the AD process for oily sludge treatment using a CHP system. The equations provided were applied to calculate the daily methane production, thermal energy potential, and energy demand, leading to a comprehensive analysis of the process's energy balance and feasibility.

3. Results and discussion

3.1. Physico-biochemical characterization of the sludge samples

Oily sludge exhibits significant variations in its physical qualities due to the heterogeneity of its chemical contents. Furthermore, the characteristics derived from one specific sludge source cannot be applied to those from a different source (Hu et al., 2013). Hence, physical-biochemical characterization has been done since it was crucial before AD (Table 2).

The high chemical oxygen demand (COD) values indicate the presence of significant organic matter in PS, suggesting a promising potential for biomethane production through AD. The COD/TS ratios also support the suitability of these substrates for the process. The TS contents are slightly higher than those found in literature, ranging from 100 to 600 g/kg TS (Jerez et al., 2021; Liu et al., 2012; Mohan and Chandrasekhar, 2011). The sludges' pH was in the neutral range with practically no variation. The HHV of the oily sludge was 3950 kcal/kg , almost similar to those found for a refinery oily sludge with an average value of 3700 kcal/kg (Jerez et al., 2021; Nazem and Tavakoli, 2017). The specific heat of the PS ranged from $2450 \text{ kJ/m}^3\cdot\text{K}$ to $2950 \text{ kJ/m}^3\cdot\text{K}$. This highlights the sludge's capacity for heat absorption, which is essential for maintaining stable temperatures during AD. This value will be used later in the energy estimation section. Such thermal properties are crucial for optimizing the digestion system's energy efficiency and overall performance.

3.2. Methane potential in batch reactors

3.2.1. Methane production at 37°C

As mentioned in the materials and methods section, all samples were tested in duplicate, following a Total Solids (TS) ratio in the digesters of $3/1$ (Inoculum/Substrate). This ratio was optimal for methane production from PS (Korai et al., 2024) and other types of waste, such as wastewater sludge (El Achkar et al., 2023).

The findings in Fig. 3A show significant trends in methane production among the various digesters over 60 days of AD at 37°C . The digesters with Inoculum + Petroleum Oily Sludge produced the highest amount of methane throughout the experiment. It started quickly and steadily increased, reaching 4.53 NL of methane by day 60. In contrast, the "Inoculum + Desalter Sludge" digesters produced almost the same amount of methane as the Inoculum Alone setup. The similarity suggests that the desalter sludge may contain components that inhibit the bacterial activity that produces methane. Factors in the desalter sludge, such as salts or other chemicals, could potentially interfere with microbial activity, reducing methane production.

The Inoculum Alone arrangement produced a continuous increase in methane, reaching around 3.58 L by the end of the 60 days. The significant difference in methane production between the digesters shows that the microbial population in the cow manure may be more successful at breaking down the organic compounds present in the petroleum oily sludge than the desalter sludge.

3.2.2. Methane production at 45°C

The study of methane production at 45°C reveals significant differences in gas yield across experimental setups compared to 37°C , as illustrated in Fig. 3B. At 45°C , all digesters produced more methane over 60 days than at 37°C . By Day 60, the Inoculum Alone digesters at 45°C had produced roughly 3.31 NL of methane, representing a 7.6% increase in gas production over the similar setup at 37°C .

Methane output for the "Inoculum + Desalter Sludge" digesters at 45°C reached roughly 3.33 NL by day 60, representing a 6.8% improvement over its performance at 37°C , indicating similar gas production trends between the two temperatures. As under 37°C , the desalter sludge showed no degradation or conversion to methane since the amount of gas recorded was almost similar to the inoculum alone.

Table 2
Components of petroleum sludge samples used in the experiments.

Substrate	COD (gO ₂ /kg)	TS (g/kg)	COD/TS	P (mg/kg)	N (mg/kg)	pH	HHV (kcal/kg)	Specific heat (kJ/m ³ K)
Oily Sludge	400 ± 25	695 ± 20	0.57	0.05	0.4	7.2	3950 ± 250	2950 ± 120
Desalter Sludge	340 ± 15	781 ± 10	0.43	0.06	0.6	7.0	3320 ± 180	2450 ± 130

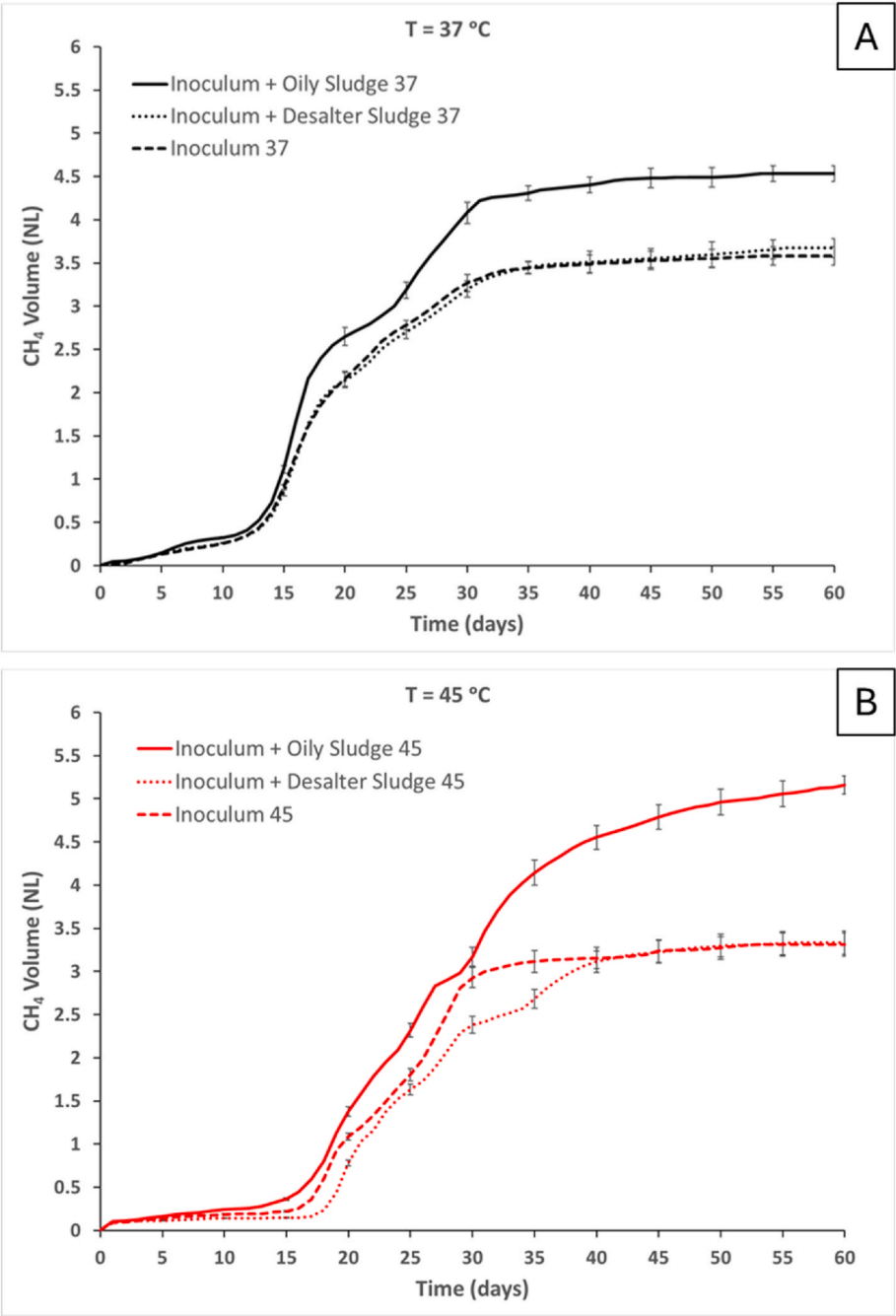


Fig. 3. Cumulative methane production from the samples at 37 °C (A) and 45 °C (B). Bars represent the average standard deviation of the experimental data.

On the other hand, the "Inoculum + Petroleum Oily Sludge" digesters at 45 °C showed a significant increase, producing roughly 5.16 NL of methane by day 60. This result reflects a 35% increase in methane generation over the performance of the same setup at 37 °C.

When the percentage increase in gas production between the two temperatures is compared, the Inoculum + Petroleum Oily Sludge configuration has the most remarkable improvement. The combination

of methane volumes and percentage increase illustrates how temperature affects methane creation. The rise in gas output across all digesters at 45 °C indicates the positive effect of higher temperatures on methane production. However, the persisting issues associated with the desalter sludge are still visible even at higher temperatures.

The significant difference in methane production between the digesters indicates that the microbial population in the inoculum is more

effective at breaking down the organic compounds present in petroleum oily sludge than desalter sludge. This observation emphasizes the importance of understanding the composition of waste materials in AD processes.

Several factors could explain the reduced methane production observed with desalter sludge.

- **High Salt Content:** Desalter sludge often contains high levels of salts, which can have inhibitory effects on methanogenic bacteria (Li et al., 2023). High salt concentrations can lead to osmotic stress, reducing microbial activity and methane production. Salts can also precipitate essential nutrients, making them unavailable to microbes.
- **Presence of Inhibitory Chemicals:** Desalter sludge may contain various chemicals used in the desalting process, such as demulsifiers, corrosion inhibitors, and other treatment chemicals. These substances can be toxic to anaerobic microbes, further inhibiting their activity and methane production (Chen et al., 2014).
- **Reduced Biodegradability:** The organic matter in desalter sludge might be less biodegradable than in petroleum oily sludge. Complex hydrocarbons and other refractory compounds in desalter sludge may not be as readily broken down by the microbial community, leading to lower methane yields.
- **Microbial Community Dynamics:** The microbial community composition in the inoculum might be more suited to degrade the organic compounds in petroleum oily sludge than those in desalter sludge. The presence of specific microbial populations that are more effective at breaking down specific substrates can significantly impact methane production.

Further research on the inhibitory components in desalter sludge is required to optimize AD methods for PS treatment. Understanding these obstacles can help refine the process and identify appropriate waste sources for efficient methane production via AD. Addressing the challenges of desalter sludge could lead to more effective treatment strategies and improved biogas yields.

3.3. Kinetics study and anaerobic biodegradability

To evaluate the anaerobic biodegradability of oily sludge, the methane production volumes from the "Petroleum Oily Sludge" digesters were first corrected by subtracting the methane production volumes from the Inoculum alone setup. The corrected data were then divided by the amount of COD present in the sample, which was determined to be 400 g COD per kg of oily sludge. To determine the biodegradability, the highest methane production obtained was divided by 350 using the formula described in the materials and methods section. Fig. 4 illustrates the experimental and modeled curves based on these calculations.

The experimental results and kinetic parameters obtained from the Modified Gompertz Model are summarized in Table 3. The model's correlation coefficients (R^2) were 0.988 for 37 °C and 0.997 for 45 °C, indicating an excellent fit of the Modified Gompertz Model to the experimental data. The experimental methane yield for oily sludge at 37 °C was 67.8 NL/kg COD, while at 45 °C, it was 135.0 NL/kg COD. This indicates a significant increase in methane production at the higher temperature, reflecting enhanced biodegradation.

The Modified Gompertz Model predicted methane yields of 69.8 NL/kg COD for 37 °C and 154.0 NL/kg COD for 45 °C. The differences between experimental and predicted yields were 3.0% and 14.0%, respectively, indicating a good fit of the model to the experimental data.

Table 3

Kinetic parameters and biodegradability of oily sludge at 37 °C and 45 °C.

Parameter	Oily Sludge 37 °C	Oily Sludge 45 °C
Experimental methane yield (NL/kg COD)	67.8	135.0
Predicted methane yield, P (NL/kg COD)	69.8	154.0
Difference between experimental and predicted gas yield (%)	3.0	14.0
Maximum methane production rate, R (NL/kg COD/day)	3.24	3.96
Residence time, λ (days)	12.4	15.4
Correlation coefficient, R^2	0.988	0.997
Experimental Biodegradability (%)	19.4	38.6
Predicted Biodegradability (%)	19.9	44.0

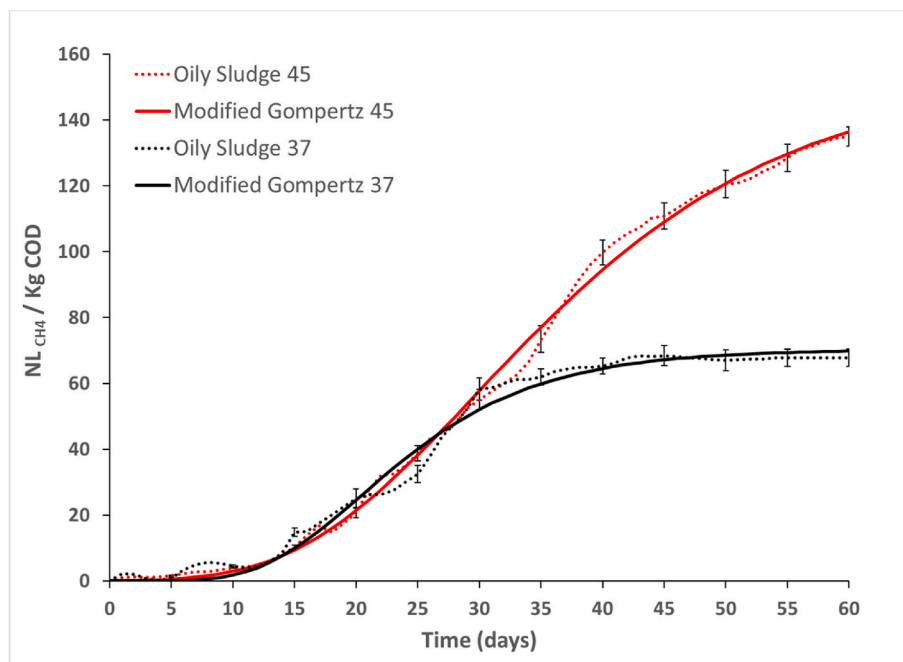


Fig. 4. Experimental and Predicted methane production (NL/Kg_{COD}) from Oily sludge samples at 37 °C and 45 °C. Bars represent the average standard deviation of the experimental data.

The maximum methane production rate (R) increased from 3.24 NL/kg COD/day at 37 °C to 3.96 NL/kg COD/day at 45 °C. This increase suggests that microbial activity and substrate conversion were more efficient at the higher temperature.

The lag phase increased from 12.4 days at 37 °C to 15.4 days at 45 °C, likely due to the initial adaptation period required by the microbial community to acclimatize to the elevated temperature. Those extended lag phase periods can be attributed to several factors. Firstly, using cow manure as the inoculum, rather than anaerobic inoculum from established anaerobic digesters, contributed to the more prolonged lag phase. In Kuwait, the non-availability of specialized anaerobic inoculum necessitated cow manure, which required additional time to adapt to the specific temperature conditions and the complex nature of the oily sludge. Secondly, the complexity of the waste itself plays a significant role. PS is a challenging substrate for AD due to its intricate composition, including various hydrocarbons and other refractory compounds. The anaerobic bacteria needed time to acclimate and establish a stable microbial community capable of efficiently degrading such complex organic matter. Overall, using cow manure as the inoculum and dealing with a complex waste substrate likely contributed to the high lag phases observed in the experiments.

The experimental biodegradability of the oily sludge from the experiments at 37 °C was found to be 19.4%, while at 45 °C, it increased to 38.6%. Considering the model-predicted methane yield, the biodegradability of the oily sludge at 37 °C was found to be 19.9%, while at 45 °C, it increased to 44.0%. The significant increase in biodegradability reported at 45 °C highlights the primary influence of increased temperatures on oily sludge biodegradation. These results are important as they reflect a previously unreported level of efficacy in the literature. Considering its complex composition and limited exploitation, achieving up to 44% biodegradation of PS is noteworthy.

Compared to other substrates, such as grape pomace, where anaerobic biodegradability of total COD ranges from 30% to 69% (El Achkar et al., 2017), reaching 40% with PS is notable. This demonstrates again the potential for AD of PS as a viable waste management and energy recovery strategy. Future studies could assess the effects of pre-treatments to increase the biodegradability of PS, potentially enhancing the AD process and improving energy recovery (El Achkar et al., 2018c).

The results demonstrate that increasing the temperature from 37 °C

to 45 °C significantly enhances oily sludge's biodegradation and methane production potential. The higher biodegradability and methane yield at 45 °C can be attributed to the accelerated microbial metabolism and enzymatic activities at elevated temperatures, which facilitate the breakdown of complex organic compounds in the sludge.

3.4. Methane production in continuous reactors

Since the highest methane yields and biodegradation rates were obtained at 45 °C, continuous AD experiments were conducted using oily sludge at that temperature, with the system operating over 120 days. Continuous reactors are critical for assessing the long-term stability and efficiency of the process. They allow for the monitoring of steady-state conditions and provide insights into the operational challenges and performance of the system under sustained loading. The methane production data, expressed as NL CH₄ per kg COD per day, is presented in Fig. 5, along with the TVA/Alkalinity ratio. This data is essential for understanding digestion's behavior and evaluating methane production's overall efficacy.

As depicted in Fig. 5, during the initial start-up period, the OLR was gradually increased to allow the microbial community to acclimatize to the oily sludge. The OLR was incremented from 0.5 Kg COD/m³/day (7 days) to 1.0 Kg COD/m³/day (7 days), then to 1.5 Kg COD/m³/day (7 days), 2.0 Kg COD/m³/day (7 days), and finally to 2.5 Kg COD/m³/day. After reaching this OLR, digesters underwent a 90-day operational period, equivalent to thrice the HRT, ensuring that the system reached a stable state, marked by consistent gas production.

Stable Production Phase (28–120 Days): From day 28 onwards, methane production increased steadily, reaching a peak of 108 NL CH₄/Kg COD/day by day 95. The system achieved consistent methane production, indicating that it had reached a stable state. After day 95, the methane production remained relatively stable, fluctuating slightly around 105–108 NL CH₄/Kg COD/day.

The maximum methane production rate observed was around 108 NL CH₄/Kg COD/day on days 95, 110, and 120, demonstrating the effectiveness of the continuous system in converting oily sludge into methane.

The TVA/Alkalinity ratio is critical for monitoring process stability in anaerobic digesters. A ratio of less than 0.4 is recommended for stable

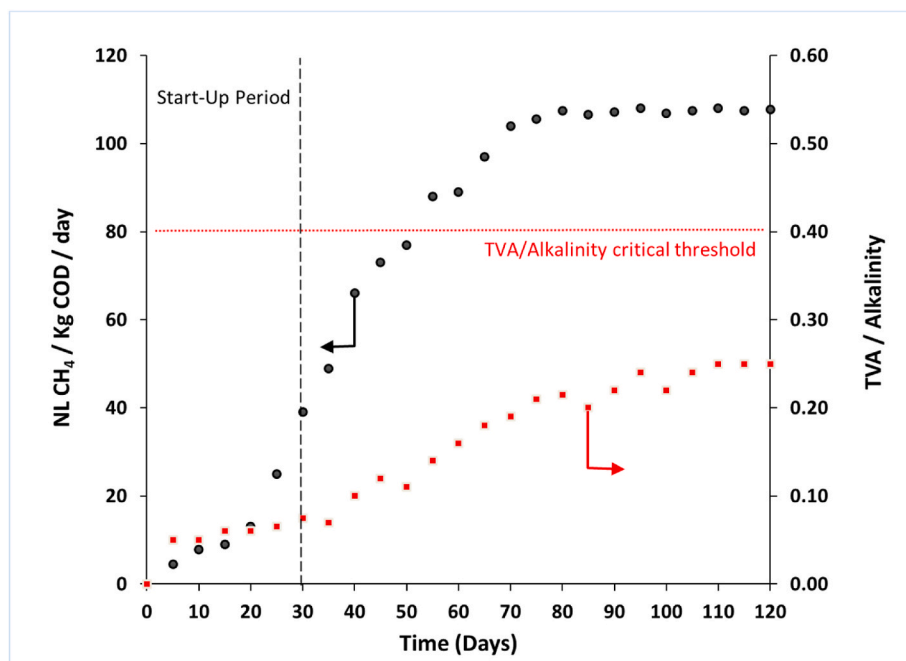


Fig. 5. Methane Production and TVA/Alkalinity Ratio in Continuous Reactors under 45 °C. Values correspond to the mean of the measurement.

operation (Callaghan et al., 2002). Fig. 5 indicates that the TVA/Alkalinity ratio remained below 0.25 throughout the 120 days, suggesting stable digestion conditions. The experiment's relatively low and stable TVA/Alkalinity ratio indicates that the reactor maintained good process stability. The highest ratio observed was 0.25, well below the threshold of 0.4, indicating that excessive volatile acids did not inhibit the process. In addition, the pH values remained within a suitable range (6.8–7.2), further confirming the stability of the AD process.

The stable methane production and low TVA/Alkalinity ratios observed over the 120 days indicate that the process can be reliably scaled up to larger systems without significant fluctuations in performance.

On another note, no foaming was observed during the continuous reactor experiments, a positive indicator of process stability. The absence of foaming suggests that the AD process was well-controlled, with a balanced organic loading rate, optimal microbial populations, and stable pH levels.

To proceed with a technical evaluation of the digester, the methane production efficiency from oily sludge was assessed by comparing batch and continuous modes. Methane production in the continuous pilot represented 80% of that obtained in the batch system, aligning with efficiencies reported in the literature, which range between 75% and 90% (El Achkar et al., 2016; Kafle and Kim, 2013; Sambusiti et al., 2013). Several factors in this study could explain the slight discrepancy in efficiency between the batch and continuous experiments.

In the batch system, the PS and microorganisms have a longer contact time, which allows for more complete degradation of the substrates. The extended exposure time enhances microbial activity and substrate breakdown, producing higher methane yields.

The difference in residence time distribution between batch and continuous systems can impact the efficiency of substrate degradation. In a batch system, all the substrate remains in the reactor for the entire experiment. In contrast, new substrate is continuously added in a continuous system, and digestate is removed, leading to a variation in residence time and potentially less complete degradation.

Finally, the mixing systems in batch and continuous reactors can also

affect the degradation efficiency. The batch system mixes the contents periodically, ensuring a uniform distribution of microorganisms and substrates. In contrast, continuous systems may experience variations in mixing efficiency, potentially leading to localized areas of lower microbial activity and reduced substrate degradation.

3.5. Energy estimation

The energy estimation analysis for the AD process and CHP system was conducted to assess the potential energy production and feasibility. The results obtained from the methane production data and subsequent calculations are summarized in Fig. 6. This diagram visualizes the energy flow, showing the theoretical thermal energy production from methane, the energy demands for heating and heat loss, and the net energy production available.

The energy estimation results demonstrate the AD process's feasibility and efficiency for oily sludge treatment using a CHP system. The significant daily methane production and net positive energy output are key indicators of the process's effectiveness.

The daily methane production of $107.8 \text{ Nm}^3 \text{ CH}_4/\text{day}$ highlights the high potential for converting oily sludge into valuable methane. The theoretical thermal energy of 3859.24 MJ/day (or 1071.83 kWh/day) provides substantial energy that can be harnessed for electricity generation and heating. The total thermal energy demand, including the energy required for heating the feedstock and covering heat loss, was calculated to be $795,421 \text{ kJ/day}$ (220.95 kWh/day). This indicates the energy required to maintain the digester's operational conditions.

The process demonstrates a positive energy balance with a net energy production of 850.88 kWh/day , confirming its feasibility and efficiency. This surplus energy can offset operational costs or be sold back to the grid, providing economic benefits.

The thermal efficiency of 68.61 MJ/day and electrical efficiency of 61.02 MJ/day indicate that a significant portion of the energy content in the biogas is effectively converted to valuable energy. These efficiencies contribute to the overall feasibility and attractiveness of the process.

Optimizing methane production by modifying the temperature in AD

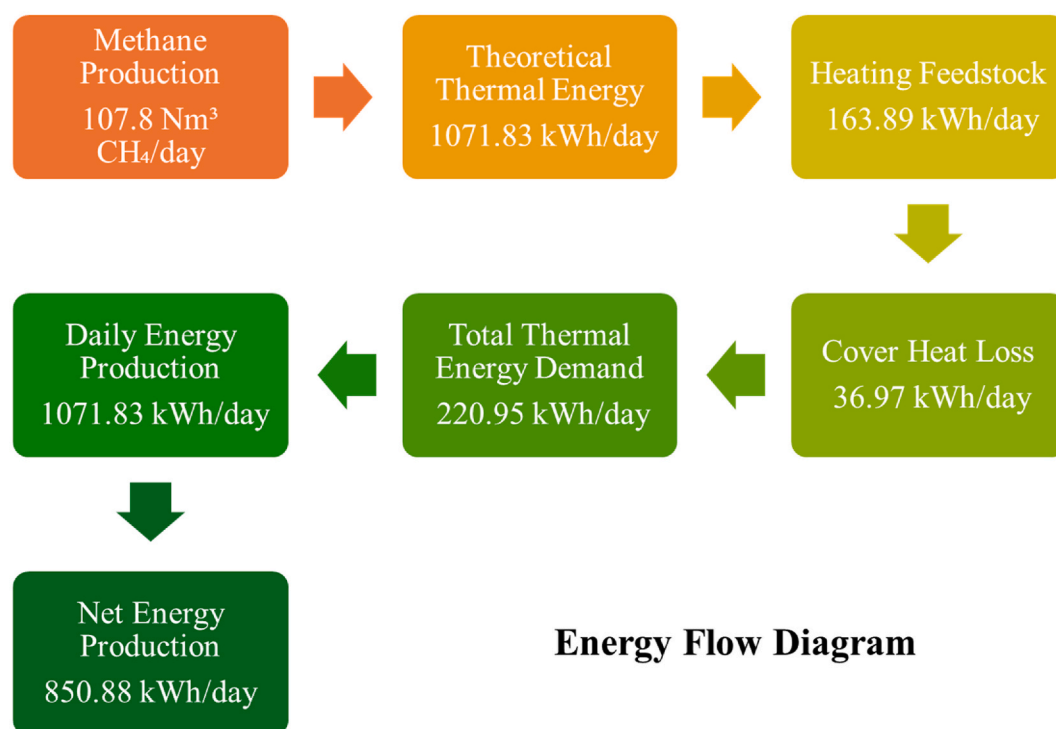


Fig. 6. Energy flow and net energy production from anaerobic digestion of petroleum sludge.

processes is crucial. Studies comparing several temperatures indicate that higher temperatures can enhance biogas production, balancing the additional energy needed for heating (Andersson et al., 2020). Utilizing excess thermal energy from biogas through a CHP system is economical to maintain optimal temperatures, though its thermal efficiency is typically limited to around 40–45% (Deng et al., 2014; Kougias and Angelidaki, 2018).

Therefore, using excess thermal energy from biogas via a CHP system increases the overall energy efficiency of the process. Capturing and utilizing the thermal energy generated during biogas production minimizes energy losses and maximizes resource utilization. Economic feasibility and practical implementation of the CHP method must be considered, including factors like energy conversion efficiency, infrastructure requirements, and operational costs.

Methane from AD as a fuel for CHP systems is a renewable energy source, reducing dependence on fossil fuels and enhancing energy sustainability. Capturing and utilizing methane from AD prevents its release into the atmosphere, providing significant environmental benefits. Additionally, the positive net energy production highlights the economic viability of the process, with surplus energy offsetting facility energy costs or providing additional revenue.

4. Conclusion

This study investigated the anaerobic digestion (AD) of petroleum sludge (PS) for bioenergy production, focusing on oily and desalter sludge from local industries in Kuwait. The anaerobic biodegradability of oily sludge improved significantly at 45 °C, increasing from 19.9% at 37 °C to 44.0% at 45 °C. Batch reactor studies revealed that the "Inoculum + Petroleum Oily Sludge" setup produced the maximum methane yield, particularly at 45 °C, confirming the beneficial effects of higher temperatures. Continuous digestion tests at 45 °C yielded stable methane generation and low TVA/Alkalinity ratios for the process scale-up, indicating high stability. The continuous reactor achieved 80% of the batch system's methane generation efficiency, likely due to extended contact time and residence time distribution in batch mode. The theoretical thermal energy from methane combustion was 1071.83 kWh/day, with a net energy output of 850.88 kWh/day, demonstrating the economic and environmental viability of the anaerobic digestion process when combined with a CHP system for oily sludge treatment.

Future research should investigate pretreatment approaches to improve the biodegradability of PS and use specific anaerobic inoculum to shorten the lag phase and increase efficiency. The promising results suggest that the process can be scaled up to industrial levels, although thorough economic and feasibility studies are required. Quantifying environmental benefits using life cycle analysis can provide detailed insights into the process's sustainability. In conclusion, this study shows that AD can treat PS while creating sustainable energy. The findings provide a solid platform for future research and development to implement sustainable waste management strategies in the petroleum industry while moving towards net-zero emissions and carbon-neutral operations.

CRedit authorship contribution statement

Jean H. El Achkar: Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rana Malhas:** Writing – review & editing, Visualization, Formal analysis, Data curation. **Faisal Albalool:** Validation, Resources, Investigation. **Abdullah Alrabaie:** Validation, Resources, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

the work reported in this paper.

Acknowledgment

The authors would like to thank the Australian University in Kuwait for supporting this research and the individuals who supplied sludge and manure samples.

Data availability

Data will be made available on request.

References

- American Public Health Association, Eaton, A.D., 2005. American water works association, water environment federation. Stand. Methods Exam. Water Wastewater 2–3. APHA-AWWA-WEF, Washington, D.C., 23rd Edition. Volume (Part 2540 B).
- Ampese, L.C., Sganzerla, W.G., Di Domenico Ziero, H., Mudhoo, A., Martins, G., Forster-Carneiro, T., 2022. Research progress, trends, and updates on anaerobic digestion technology: a bibliometric analysis. *J. Clean. Prod.* 331, 130004. <https://doi.org/10.1016/j.jclepro.2021.130004>.
- Andersson, J., Helander-Claesson, J., Olsson, J., 2020. Study on reduced process temperature for energy optimisation in mesophilic digestion: a lab to full-scale study. *Appl. Energy* 271, 115108. <https://doi.org/10.1016/j.apenergy.2020.115108>.
- Brauer, H.B., Khan, J., 2021. Diffusion of Biogas for Freight Transport in Sweden: A User Perspective 127738.
- Buffiere, P., Frederic, S., Marty, B., Delgenes, J.-P., 2008. A comprehensive method for organic matter characterization in solid wastes in view of assessing their anaerobic biodegradability. *Water Sci. Technol. J. Int. Assoc. Water Pollut. Res.* 58, 1783–1788. <https://doi.org/10.2166/wst.2008.517>.
- Callaghan, F.J., Wase, D.A.J., Thayani, K., Forster, C.F., 2002. Continuous co-digestion of cattle slurry with fruit and vegetable wastes and chicken manure. *Biomass Bioenergy* 22, 71–77. [https://doi.org/10.1016/S0961-9534\(01\)00057-5](https://doi.org/10.1016/S0961-9534(01)00057-5).
- Chen, J.L., Ortiz, R., Steele, T.W.J., Stuckey, D.C., 2014. Toxicants inhibiting anaerobic digestion: a review. *Biotechnol. Adv.* 32, 1523–1534. <https://doi.org/10.1016/j.biotechadv.2014.10.005>.
- Chen, Y.-C., 2018. Evaluating greenhouse gas emissions and energy recovery from municipal and industrial solid waste using waste-to-energy technology. *J. Clean. Prod.* 192, 262–269. <https://doi.org/10.1016/j.jclepro.2018.04.260>.
- Deng, L., Yang, H., Liu, G., Zheng, D., Chen, Z., Liu, Y., Pu, X., Song, L., Wang, Z., Lei, Y., 2014. Kinetics of temperature effects and its significance to the heating strategy for anaerobic digestion of swine wastewater. *Appl. Energy* 134, 349–355. <https://doi.org/10.1016/j.apenergy.2014.08.027>.
- El Achkar, J., 2017. Méthanisation de marc de raisin. Caractérisation et optimisation du procédé et des prétraitements (These de doctorat). Lorient.
- El Achkar, J.H., 2022. Sustainable solid waste management: towards a complete and effective strategy. *Arab J. STI Policies* 3, 9–17. <https://doi.org/10.21608/ARABSTI.2023.291066>.
- El Achkar, J.H., Baydoun, A., Salameh, D., Louka, N., Hobaika, Z., Maroun, R.G., 2018a. Can coffee grounds be considered as a potential for green energy production? In: 2018 4th International Conference on Renewable Energies for Developing Countries (REDEC). Presented at the 2018 4th International Conference on Renewable Energies for Developing Countries (REDEC), pp. 1–6. <https://doi.org/10.1109/REDEC.2018.8598105>.
- El Achkar, J.H., El Joahari, A., Nassreddine, C., Mgharbel, M., Izmerly, Y., 2023. Anaerobic digestion of wastewater sludge for improved energy recovery: alkaline pretreatment impact, digestate quality assessment, and reactor design. *Arabian J. Sci. Eng.* <https://doi.org/10.1007/s13369-023-08068-1>.
- El Achkar, J.H., Husain, A.B., Alotaibi, N., Alhaddad, N., Alamgir, T., Alshamali, H., Alshammari, Y., Almuhamma, M., Albekheet, A., Alenezi, K., Alsaba, M.T., 2022. Could petroleum sludge be used to produce biomethane as a renewable energy source? Presented at the ADIPEC. OnePetro. <https://doi.org/10.2118/210953-MS>.
- El Achkar, J.H., Lendormi, T., Hobaika, Z., Salameh, D., Louka, N., Maroun, R.G., Lanoisellé, J.-L., 2017. Anaerobic digestion of nine varieties of grape pomace: correlation between biochemical composition and methane production. *Biomass Bioenergy* 107, 335–344. <https://doi.org/10.1016/j.biombioe.2017.10.030>.
- El Achkar, J.H., Lendormi, T., Hobaika, Z., Salameh, D., Louka, N., Maroun, R.G., Lanoisellé, J.-L., 2016. Anaerobic digestion of grape pomace: biochemical characterization of the fractions and methane production in batch and continuous digesters. *Waste Manag.* 50, 275–282. <https://doi.org/10.1016/j.wasman.2016.02.028>.
- El Achkar, J.H., Lendormi, T., Salameh, D., Louka, N., Maroun, R.G., Lanoisellé, J.-L., Hobaika, Z., 2018b. Anaerobic digestion of grape pomace: effect of the hydraulic retention time on process performance and fibers degradability. *Waste Manag.* 71, 137–146. <https://doi.org/10.1016/j.wasman.2017.11.005>.
- El Achkar, J.H., Lendormi, T., Salameh, D., Louka, N., Maroun, R.G., Lanoisellé, J.-L., Hobaika, Z., 2018c. Influence of pretreatment conditions on lignocellulosic fractions and methane production from grape pomace. *Bioresour. Technol.* 247, 881–889. <https://doi.org/10.1016/j.biortech.2017.09.182>.
- El Achkar, J.H., Rohayem, C., Salameh, D., Louka, N., Maroun, R.G., Hobaika, Z., 2018d. Olive pomace, a source of green energy using anaerobic digestion. In: 2018 4th International Conference on Renewable Energies for Developing Countries (REDEC).

- Presented at the 2018 4th International Conference on Renewable Energies for Developing Countries (REDEC), pp. 1–6. <https://doi.org/10.1109/REDEC.2018.8598079>.
- El Achkar, J.H., Ziade, R., Louka, N., Maroun, R.G., Hobaika, Z., 2020. Treatment of dairy waste by anaerobic digestion to produce methane as green energy. In: 2020 5th International Conference on Renewable Energies for Developing Countries (REDEC). Presented at the 2020 5th International Conference on Renewable Energies for Developing Countries (REDEC), pp. 1–6. <https://doi.org/10.1109/REDEC49234.2020.9163848>.
- Ezemagu, I.G., Ejimofor, M.I., Menkiti, M.C., 2020. Thermodynamic studies of anaerobic digestion of post coagulation sludge from petroleum produced water and cow dung. *Curr. Res. Green Sustain. Chem.* 3, 100037. <https://doi.org/10.1016/j.crgsc.2020.100037>.
- Haak, L., Roy, R., Pagilla, K., 2016. Toxicity and biogas production potential of refinery waste sludge for anaerobic digestion. *Chemosphere* 144, 1170–1176. <https://doi.org/10.1016/j.chemosphere.2015.09.099>.
- Hakawati, R., Smyth, B.M., McCullough, G., De Rosa, F., Rooney, D., 2017. What is the most energy efficient route for biogas utilization: heat, electricity or transport? *Appl. Energy* 206, 1076–1087. <https://doi.org/10.1016/j.apenergy.2017.08.068>.
- Hu, G., Li, J., Zeng, G., 2013. Recent development in the treatment of oily sludge from petroleum industry: a review. *J. Hazard Mater.* 261, 470–490. <https://doi.org/10.1016/j.jhazmat.2013.07.069>.
- Janajreh, I., Alshehi, A., Elagroudy, S., 2020. Anaerobic co-digestion of petroleum hydrocarbon waste and wastewater treatment sludge. *Int. J. Hydrogen Energy* 45, 11538–11549. <https://doi.org/10.1016/j.ijhydene.2018.05.100>.
- Jerez, S., Ventura, M., Molina, R., Pariente, M.I., Martínez, F., Melero, J.A., 2021. Comprehensive characterization of an oily sludge from a petrol refinery: a step forward for its valorization within the circular economy strategy. *J. Environ. Manag.* 285, 112124. <https://doi.org/10.1016/j.jenvman.2021.112124>.
- Johnson, O.A., Affam, A.C., 2019. Petroleum sludge treatment and disposal: a review. *Environ. Eng. Res.* 24, 191–201. <https://doi.org/10.4491/eer.2018.134>.
- K, B., Pilli, S., Rao, P.V., Tyagi, R.D., 2024. Predictive modelling of methane yield in biochar-amended cheese whey and septage co-digestion: exploring synergistic effects using Gompertz and neural networks. *Chemosphere* 353, 141558. <https://doi.org/10.1016/j.chemosphere.2024.141558>.
- Kafle, G.K., Kim, S.H., 2013. Anaerobic treatment of apple waste with swine manure for biogas production: batch and continuous operation. *Appl. Energy* 103, 61–72. <https://doi.org/10.1016/j.apenergy.2012.10.018>.
- Kankia, M.U., Baloo, L., Danlami, N., Mohammed, B.S., Haruna, S., Abubakar, M., Jagaba, A.H., Sayed, K., Abdulkadir, I., Salihi, I.U., 2021. Performance of fly ash-based inorganic polymer mortar with petroleum sludge ash. *Polymers* 13, 4143. <https://doi.org/10.3390/polym13234143>.
- Kardena, Q.H.E., 2015. Petroleum oil and gas industry waste treatment; common practice in Indonesia. *J. Pet. Environ. Eng.* <https://doi.org/10.4172/2157-7463.1000241>, 2015.
- Klenert, D., Funke, F., Mattauch, L., O'Callaghan, B., 2020. Five lessons from COVID-19 for advancing climate change mitigation. *Environ. Resour. Econ.* 76, 751–778. <https://doi.org/10.1007/s10640-020-00453-w>.
- Korai, M.S., Pinjaro, M.A., Bhatti, Z.A., Herraprantant, E.H., Jatoti, M., Shar, M.A., Alhazaa, A., 2024. Co-digestion of petroleum sludge and Buffalo dung by batch anaerobic digestion system. *J. Ecol. Eng.* 25, 120–127. <https://doi.org/10.12911/22998993/186898>.
- Kougiass, P.G., Angelidakis, I., 2018. Biogas and its opportunities—a review. *Front. Environ. Sci. Eng.* 12, 14. <https://doi.org/10.1007/s11783-018-1037-8>.
- Kunatsa, T., Xia, X., 2022. A review on anaerobic digestion with focus on the role of biomass co-digestion, modelling and optimisation on biogas production and enhancement. *Bioresour. Technol.* 344, 126311. <https://doi.org/10.1016/j.biortech.2021.126311>.
- Li, J., Xu, X., Chen, C., Xu, L., Du, Z., Gu, L., Xiang, P., Shi, D., Huangfu, X., Liu, F., 2023. Conductive materials enhance microbial salt-tolerance in anaerobic digestion of food waste: microbial response and metagenomics analysis. *Environ. Res.* 227, 115779. <https://doi.org/10.1016/j.envres.2023.115779>.
- Liu, W., Wang, X., Wu, L., Chen, M., Tu, C., Luo, Y., Christie, P., 2012. Isolation, identification and characterization of *Bacillus amyloliquefaciens* BZ-6, a bacterial isolate for enhancing oil recovery from oily sludge. *Chemosphere* 87, 1105–1110. <https://doi.org/10.1016/j.chemosphere.2012.01.059>.
- Mohan, S.V., Chandrasekhar, K., 2011. Self-induced bio-potential and graphite electron accepting conditions enhances petroleum sludge degradation in bio-electrochemical system with simultaneous power generation. *Bioresour. Technol.* 102, 9532–9541. <https://doi.org/10.1016/j.biortech.2011.07.038>.
- Murungi, P.I., Sulaimon, A.A., 2022. Petroleum sludge treatment and disposal techniques: a review. *Environ. Sci. Pollut. Res.* 29, 40358–40372. <https://doi.org/10.1007/s11356-022-19614-z>.
- Nazem, M.A., Tavakoli, O., 2017. Bio-oil production from refinery oily sludge using hydrothermal liquefaction technology. *J. Supercrit. Fluids* 127, 33–40. <https://doi.org/10.1016/j.supflu.2017.03.020>.
- Paul Choudhury, S., Saha, B., Haq, I., Kalamdhad, A.S., 2022. 17 - use of petroleum refinery sludge for the production of biogas as an alternative energy source: a review. In: Hussain, C., Hait, S. (Eds.), *Advanced Organic Waste Management*. Elsevier, pp. 277–297. <https://doi.org/10.1016/B978-0-323-85792-5.00021-6>.
- Ritchie, H., Roser, M., 2020. CO₂ and Greenhouse Gas Emissions. *Our World Data*.
- Roy, R., Haak, L., Li, L., Pagilla, K., 2016. Anaerobic digestion for solids reduction and detoxification of refinery waste streams. *Process Biochem.* 51, 1552–1560. <https://doi.org/10.1016/j.procbio.2016.08.006>.
- Sambusiti, C., Ficari, E., Malpei, F., Steyer, J.P., Carrère, H., 2013. Benefit of sodium hydroxide pretreatment of ensiled sorghum forage on the anaerobic reactor stability and methane production. *Bioresour. Technol.* 144, 149–155. <https://doi.org/10.1016/j.biortech.2013.06.095>.
- Szaja, A., Montusiewicz, A., 2019. Enhancing the co-digestion efficiency of sewage sludge and cheese whey using brewery spent grain as an additional substrate. *Bioresour. Technol.* 291, 121863. <https://doi.org/10.1016/j.biortech.2019.121863>.
- Szaja, A., Montusiewicz, A., Lebioccka, M., 2021. The energetic aspect of organic wastes addition on sewage sludge anaerobic digestion: a laboratory investigation. *Energies* 14, 6113. <https://doi.org/10.3390/en14196113>.
- Van, D.P., Fujiwara, T., Tho, B.L., Toan, P.P.S., Minh, G.H., 2020. A review of anaerobic digestion systems for biodegradable waste: configurations, operating parameters, and current trends. *Environ. Eng. Res.* 25, 1–17. <https://doi.org/10.4491/eer.2018.334>.
- Wang, Q., Liang, Y., Zhao, P., Li, Q.X., Guo, S., Chen, C., 2016. Potential and optimization of two-phase anaerobic digestion of oil refinery waste activated sludge and microbial community study. *Sci. Rep.* 6, 38245. <https://doi.org/10.1038/srep38245>.
- Yaashikaa, P.R., Kumar, P.S., Saravanan, A., Varjani, S., Ramamurthy, R., 2020. Bioconversion of municipal solid waste into bio-based products: a review on valorisation and sustainable approach for circular bioeconomy. *Sci. Total Environ.* 748, 141312. <https://doi.org/10.1016/j.scitotenv.2020.141312>.
- Zamri, M.F.M.A., Hasmady, S., Akhiar, A., Ideris, F., Shamsuddin, A.H., Mofijur, M., Fattah, I.M.R., Mahlia, T.M.I., 2021. A comprehensive review on anaerobic digestion of organic fraction of municipal solid waste. *Renew. Sustain. Energy Rev.* 137, 110637. <https://doi.org/10.1016/j.rser.2020.110637>.



Sustainable conversion of petroleum sludge to methane: A study on anaerobic biodegradability in batch and continuous systems

Jean H. El Achkar^{*}, Rana Malhas, Faisal Albalool, Abdullah Alrabaie

Petroleum Engineering Department, College of Engineering, Australian University, West Mishref, Safat, 13015, Kuwait

ARTICLE INFO

Keywords:

Anaerobic digestion
Petroleum sludge
Methane production
Biodegradability
Kinetic modeling
Batch reactor
Continuous reactor

ABSTRACT

This study investigates the anaerobic digestion of petroleum sludge from Kuwait's oil and gas industry to promote bioenergy production and waste management. Experiments were conducted at 37 °C and 45 °C in batch reactors using local cow manure as inoculum, following a Total Solids (TS) ratio in the digesters of 3/1 (Inoculum/Substrate). The batch study included three experimental groups: inoculum alone, inoculum with oily sludge, and inoculum with desalter sludge, each tested in duplicate. The inoculum with the oily sludge group achieved the highest methane yield, producing 5.16 L by day 60 at 45 °C. This represents a 35% increase in methane production compared to the yield at 37 °C. The Modified Gompertz Model provided a robust fit to the experimental data, predicting methane yields of 69.8 NL/kg COD at 37 °C and 154.0 L/kg COD at 45 °C. The anaerobic biodegradability of oily sludge improved significantly under higher temperatures, with rates increasing from 19.9% at 37 °C to 44% at 45 °C. Continuous digestion experiments at 45 °C over 120 days, under an HRT of 30 days and an OLR of 2.5 Kg COD/m³/day, revealed stable methane production during the steady-state phase, peaking at 108 NL CH₄/kg COD/day. Energy estimation results indicated a theoretical thermal energy potential of 1071.83 kWh/day, with a net energy production of 850.88 kWh/day. The total thermal energy demand for the process was 220.95 kWh/day, underscoring the process's efficiency. This study offers valuable insights into optimizing anaerobic digestion for petroleum sludge, demonstrating substantial improvements in biomethane production and energy recovery. The findings provide a foundation for sustainable waste management strategies in the petroleum industry, contributing to net-zero emissions and carbon-neutral goals.

1. Introduction

The urgency of mitigating climate change effects and promoting sustainable development has become a global concern (Klenert et al., 2020). Climate change is primarily driven by nonrenewable fuels and the consequent greenhouse gas (GHG) emissions, which pose severe environmental and existential threats (Brauer and Khan, 2021). Improper disposal of industrial byproducts further exacerbates GHG emissions (Chen, 2018). Waste disposal contributes to 6% of global GHG emissions, while fossil fuels accounted for 93% of global CO₂ emissions in 2020 (Ritchie and Roser, 2020). Consequently, waste management is a critical focus for industrial sectors striving to meet the United Nations' Sustainable Development Goals (SDGs).

Innovative technologies that facilitate optimal waste management and energy recovery are essential for sustainable bio-economy development (El Achkar, 2022; Yaashikaa et al., 2020). The transition from

fossil fuels to renewable energy sources is imperative. Bioenergy recovery from solid waste (waste-to-energy) can enhance operational profitability, minimize environmental impacts, and reduce GHG emissions (Van et al., 2020).

The petroleum industry generates substantial amounts of Petroleum Sludge (PS) during oil exploration, production, refining, and effluent treatment (El Achkar et al., 2022; Jerez et al., 2021). PS consists of polycyclic aromatic hydrocarbons, benzene homologs, oil, grease, and various toxic metals and organic chemicals (Kankia et al., 2021). This hazardous composition makes PS cytogenic, mutagenic, and carcinogenic (Johnson and Affam, 2019). Improper disposal of PS can lead to environmental contamination and health hazards. Despite existing treatment technologies, the high production volume and potential dangers of PS necessitate effective and green treatment solutions.

Current PS treatment technologies include incineration, oxidation, stabilization, and biodegradation (Murungi and Sulaimon, 2022). Each

^{*} Corresponding author.

E-mail address: j.achkar@au.edu.kw (J.H. El Achkar).

<https://doi.org/10.1016/j.geoen.2025.213816>

Received 2 June 2024; Received in revised form 28 July 2024; Accepted 4 March 2025

Available online 5 March 2025

2949-8910/© 2025 Elsevier B.V. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

method has challenges, such as GHG emissions, toxic leachate infiltration, and heavy metal accumulation. Thermochemical and solidification treatments are extensively used to treat solid petroleum waste, although biological treatment is not well documented in the literature. One cause is a lack of "know-how" about the digestion of such effluent and its favorable biodegradation conditions (Kardena, 2015). Recycling PS into valuable products or processing it through environmentally friendly methods like composting or Anaerobic Digestion (AD) has become crucial (El Achkar, 2022).

AD is a biological process for managing organic waste and recovering bioenergy through microbial digestion without oxygen (Ampese et al., 2022; Zamri et al., 2021). This process produces biogas, primarily methane, which can be used for heat and electricity generation, reducing the reliance on fossil fuels (Hakawati et al., 2017). AD is considered one of the best environmentally friendly alternatives for organic waste management due to its reduced environmental footprint, high energy recovery potential, and biofertilizer production (El Achkar et al., 2018a, 2018d, 2020).

Although several studies have demonstrated the potential for biogas production from refinery wastewater, research on bioenergy production from PS through AD is limited (Haak et al., 2016; Paul Choudhury et al., 2022; Roy et al., 2016; Wang et al., 2016). Given the increasing demand for crude oil and the finite nature of fossil fuel reserves, it is crucial to explore sustainable energy sources. Converting PS into a green energy source through AD could optimize petroleum production, promote sustainable development, and mitigate environmental risks (El Achkar et al., 2022).

A study found that co-digesting 60% petroleum hydrocarbon waste with 40% wastewater treatment sludge at 35 °C in batch reactors maximized biogas production (Janajreh et al., 2020). Additionally, post-coagulation sludge from petroleum-produced water showed potential as a substrate for biogas generation when co-digested with cow manure (Ezemagu et al., 2020). A recent study examined the biochemical methane potential of buffalo dung mixed with PS in ratios of 1:1, 1.5:0.5, and 0.5:1.5. The highest methane production was obtained at a 1.5:0.5 ratio. The results suggest that this ratio is the most effective for enhancing methane production (Korai et al., 2024).

Given the gaps in the literature, this study explores the AD of PS for bioenergy production. Previous research has not thoroughly assessed methane production from PS in both batch and continuous reactors, evaluated the process at different temperatures, or tested various types of sludge. This study focuses on two types of PS samples selected from Kuwait's local oil and gas industry: oily sludge and desalter sludge. Oily sludge accumulates in storage tanks, separators, and other equipment where oil-water separation occurs. Desalter sludge is produced during the desalting process in refineries, where crude oil is treated to remove salts and impurities before further refining. Both types of sludge are generated in significant quantities during petroleum processes, although exact amounts vary with production levels. These two sludge types represent the primary categories of PS and often remain unvalorized, posing a significant waste management challenge. This study aims to enhance the understanding of AD for treating these prevalent forms of petroleum refinery waste, providing valuable insights for sustainable waste management in the industry. Consequently, the primary objectives of this study are (1) to assess the physical-biochemical characterization of the sludge samples (oily and desalter sludge) obtained from local industries in Kuwait, (2) to evaluate methane production from the samples using cow manure as inoculum at two different temperatures (37 °C and 45 °C), (3) to perform a kinetic study to understand the methane production dynamics, (4) to extrapolate the study to continuous reactors for better scalability, and (5) to conduct an energy estimation study for the AD process and Combined Heat and Power (CHP) system. This study provides novel insights into the AD of PS and its potential for bioenergy production, addressing gaps in the existing literature.

2. Materials and methods

2.1. Raw materials

Petroleum Sludge (PS) samples were obtained from Kuwait's local oil and gas industry. Two types of sludges were collected: 1) Oily Sludge deposited in tanks and 2) Desalter Sludge deposited in desalter units. Samples were transported and kept in the lab at ambient temperature until used. Before the AD tests, the inoculum (cow manure) was collected from a local dairy farm in Kuwait.

2.2. Analytical methods

According to APHA standard procedures, PS samples were examined for TS (American Public Health Association et al., 2005). The pH was monitored using a WTW pH meter model Multi 340i. In addition, the Chemical Oxygen Demand (COD), Total Phosphate P, and total Nitrogen N were also determined using UNI 10780. The Higher Heating Value (HHV) was estimated utilizing a Plain Jacket Bomb Calorimeter (model PARR 1341). A differential scanning calorimeter (Mettler Toledo DSC823) was used to determine the specific heat of PS. All analyses were performed in triplicate.

2.3. Biochemical methane potential (BMP) measurement

The Biochemical Methane Potential (BMP) tests were conducted using the Automatic Methane Potential Test System (AMPTS, Bioprocess Control, Sweden) (Fig. 1). This system is designed for online measurement of ultra-low biomethane flows generated from the AD of degradable wastes. The AMPTS II Light enables multiple anaerobic batch fermentation tests, accommodating up to six test vials. It facilitates BMP tests with integrated sampling, analysis, recording, and report generation.

2.3.1. Sample incubation

Small amounts of sample mixed with anaerobic inoculum were incubated at the desired temperature in up to six vials in the sample incubation unit. A slow-rotating agitator mixed the solution in each vial to ensure uniformity. The recurring biogas production was monitored to estimate the AD activity within each vial.

2.3.2. CO₂ absorption unit

To separate carbon dioxide (CO₂) from biogas, absorption using sodium hydroxide (NaOH) was employed. The NaOH reacts with CO₂ to form sodium carbonate (Na₂CO₃) and water, increasing the biogas's methane (CH₄) concentration. This method ensures a higher methane purity (up to 99%) by removing CO₂.

2.3.3. Gas volume measurement

The volume of methane gas produced after CO₂ absorption was measured using a multi-flow cell device. This device accurately measures the volume of methane passing through it, providing reliable data on methane production.

2.3.4. Temperature selection

The AD experiments were conducted at two different temperatures: 37 °C and 45 °C. While 37 °C is commonly used for mesophilic AD, 45 °C was selected due to its alignment with the average temperature during Kuwait's hot months. This intermediate temperature leverages the benefits of higher temperature digestion, such as enhanced hydrolysis and increased methane production, without the high energy costs of maintaining a thermophilic temperature of 55 °C. Operating at 45 °C minimizes the need for additional heating, reducing energy consumption and making the process more economical and environmentally friendly. This approach provides insights into the efficiency of AD under realistic local conditions, highlighting the potential for sustainable



Fig. 1. AMPTS II setup for batch experiments, including the sample incubation unit, CO₂ absorption unit, and gas volume measurement unit connected to a computer for live monitoring.

bioenergy production in similar climatic regions.

2.3.5. Inoculum preparation

Local cow manure was used as the inoculum due to its availability, cost-effectiveness, and established use in anaerobic digestion studies. Additionally, in the absence of industrial anaerobic digesters in Kuwait, cow manure is the best available source of anaerobic bacteria. It contains a diverse microbial community essential for facilitating the anaerobic digestion process. The manure underwent a pretreatment process where it was first sieved through a 300 μm sieve to remove large particles and then diluted with water to achieve a Total Solids (TS) rate of 5%. The COD level of the obtained inoculum was approximately 50 gO₂/kg. The methane production from the cow manure alone (used as a control) was measured separately and subtracted from the total methane production observed in the sludge groups. This approach allows the determination of the exact methane production from the sludge alone.

2.3.6. Digesters composition

The composition of the digesters used in the AMPTS experiments under 37 °C and 45 °C is detailed in Table 1. The weights of manure and sludge, along with their total solids' percentage and inoculum-to-sludge ratio, were carefully measured to ensure consistency across all experiments. The exact composition was maintained for experiments conducted at both temperature settings, 37 and 45 °C.

The study was designed with replicates to ensure the reliability and

robustness of the results. Each experimental group was tested using duplicate reactors. This approach was taken to account for potential variability and to provide more convincing and accurate results. Using replicates allows for verifying the consistency of the observed trends in methane production and biodegradability.

2.3.7. Biodegradability calculation

To evaluate the anaerobic biodegradability of the sludge, the highest volume of methane produced was used to calculate the biodegradability percentage. The following formula was applied:

$$\text{Biodegradability \%} = \frac{\text{Highest methane production of sludge (L)}}{\text{COD in sample (Kg)}} \times \frac{1 \text{ (Kg)}}{350 \text{ (L)}} \times 100$$

(Eq. 1)

In this formula, 350 represents the theoretical maximum methane yield of 350 NL CH₄/kg COD under standard temperature and pressure conditions (0 °C, 1013 hPa) (Buffiere et al., 2008).

2.4. Kinetics modeling

The kinetics of methane production in batch mode during the AD of PS were modeled using the Modified Gompertz Model. The Modified Gompertz Model is widely used in biogas production studies because it accurately describes the cumulative methane production curve in batch AD tests (Kunatsa and Xia, 2022). It accounts for the initial lag, exponential growth, and stationary phases of microbial activity, providing a comprehensive understanding of the digestion kinetics. Compared to the original Gompertz Model, the Modified Gompertz Model incorporates the maximum methane production rate (R), making it more suitable for predicting methane production. Moreover, the inclusion of the lag phase (λ) allows for better fitting of experimental data, especially in cases where there is a delay in microbial activity due to acclimatization or other factors (K et al., 2024).

The following equation represents the Modified Gompertz Model:

$$\text{BMP}_i = P \times \exp \left\{ - \exp \left[\left(\frac{R \times e}{P} \right) \times (\lambda - t) + 1 \right] \right\} \quad (\text{Eq. 2})$$

where.

- BMP_i is the biochemical potential of accumulated methane (L/kg_{COD}),

Table 1
Composition of digesters used in the AMPTS experiments, under 37 and 45 °C.

Digesters	Total Solids (TS) of the substrate (%)	Manure weight (g)	Inoculum/Sludge Ratio (weight of TS)	Sludge weight (g)	Final TS in each digester (%)
(1, 2) ^a Inoculum	5.0	1600	3/1	–	5.0
(3, 4) ^a Desalter Sludge	78.1	1600	3/1	34.1	6.52
(5, 6) ^a Oily Sludge	69.5	1600	3/1	38.4	6.51

^a Each experimental group consists of two samples to ensure the reliability of the results. Samples 1 and 2 are duplicates for the cow manure (inoculum) group, samples 3 and 4 for the cow manure and desalter sludge group, and samples 5 and 6 for the cow manure and oily sludge group.

- P is the maximum value of BMP recorded at the end of the test (L/kg_{COD}),
- R is the maximum methane production rate (L/kg_{COD}/day),
- λ is the lag phase time (days),
- t is the time (days),
- e is Euler's number (approximately 2.71828).

2.5. Methane production in continuous reactors

The system established for continuous methane production measurement includes three central components. The incubation unit comprised a thermostatic water bath housing 2 L digesters containing cow manure and oily PS (Fig. 2). The continuous reactor has two sealable tubes, one for extracting the digestate and the other for introducing the feed. Each digester was agitated daily to ensure optimal mixing (El Achkar, 2017).

The biogas generated was channeled through a connecting tube from the incubation unit to the CO₂ fixation unit, consisting of a 6 M NaOH solution to capture CO₂, with thymolphthalein, an acid-base pH indicator. Consequently, the methane generated was measured in the third unit using water displacement.

This experimental setup was subjected to a distinct temperature setting of 45 °C. The uniform oily sludge samples served as the feedstock for all trials. A daily routine of feeding and extraction was followed based on an HRT of 30 days and a final OLR set at 2.5 Kg COD/m³/day. The alkalinity and total volatile acidity (TVA) were also determined per the standardized procedure (El Achkar, 2017).

During the start-up period (0–28 days), the OLR was gradually increased to allow the microbial community to acclimatize to the oily sludge. The OLR was incremented from 0.5 Kg COD/m³/day (7 days) to 1.0 Kg COD/m³/day (7 days), then to 1.5 Kg COD/m³/day (7 days), 2.0 Kg COD/m³/day (7 days), and finally to 2.5 Kg COD/m³/day. After reaching this OLR, digesters underwent a 90-day operational period, equivalent to thrice the HRT, ensuring the system reached a stable state, marked by stable gas production (El Achkar et al., 2018b).

2.6. Energy estimation methodology

The energy estimation for the AD process and the Combined Heat and Power (CHP) system was performed using an adapted methodology from the literature (Szaja et al., 2021; Szaja and Montusiewicz, 2019). The analysis involves calculating the daily methane production, the theoretical thermal energy obtained from methane combustion, and the thermal energy required to heat the digester and cover heat losses. The equations used in the calculations and their meanings are detailed

below.

2.6.1. Methane production

The daily methane production (Q_{CH_4}) is calculated using the methane yield (Y_m) and the solids load (L).

$$Q_{CH_4} = Y_m \times L \quad (\text{Eq. 3})$$

where.

- Q_{CH_4} is the daily methane production (m³ CH₄/day).
- Y_m is the methane yield (m³ CH₄/kg COD).
- L is the total load of chemical oxygen demand (COD) in the feedstock (kg COD/day).

2.6.2. Thermal energy

The theoretical amount of thermal energy (Q_t) obtainable from the combustion of methane is given by:

$$Q_t = Q_{CH_4} \times Q_i \quad (\text{Eq. 4})$$

where.

- Q_t is the theoretical thermal energy (MJ/day).
- Q_i is the heating value of methane (35.8 MJ/m³ CH₄).

Thermal Energy Demand:

Two components are considered to determine the thermal energy demand: the energy required for heating the feedstock (Q_1) and the energy necessary to cover the heat loss through the digester walls (Q_2).

a Thermal Energy Required for Heating the Feedstock:

$$Q_1 = V_{os} \times (T - T_{feed}) \times C_{PS} \quad (\text{Eq. 5})$$

where.

- Q_1 is the thermal energy required for heating the feedstock (kJ/day).
- V_{os} is the feedstock flow rate (m³/day).
- T is the AD temperature (K).
- T_{feed} is the feedstock temperature (K).
- C_{PS} is the specific heat of PS (2950 kJ/m³ K).
- b Thermal Energy Required to Cover Heat Loss:

$$Q_2 = 24 \times (T - T_{air}) \times U \times F \quad (\text{Eq. 6})$$

where.

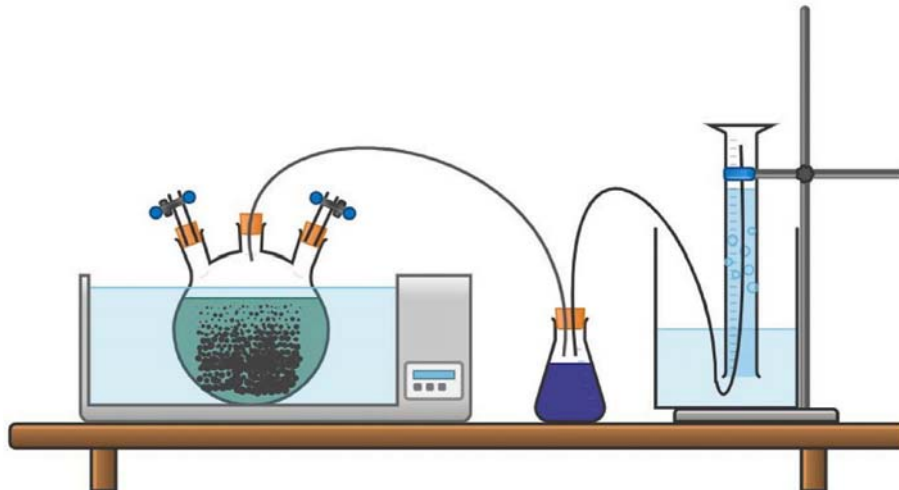


Fig. 2. Setup used for monitoring methane production in continuous mode.

- Q_2 is the thermal energy required to cover heat loss (kJ/day).
 - T_{air} is the ambient temperature (K).
 - U is the heat loss coefficient by permeation through the walls of the digester ($4.0 \text{ kJ/m}^2 \text{ h K}$).
 - F is the surface area of the digester walls (m^2).
- The surface area of the digester walls (F)

The surface area of the digester walls (F) is calculated using the following equation:

$$F = 3.17 \times D^2 \quad (\text{Eq. 7})$$

where.

- D is the diameter of the cylindrical part of the digester (m).

Total Thermal Energy Demand:

The total thermal energy demand (Q_c) is calculated by combining (Q_1) and (Q_2) with a margin factor of 1.1:

$$Q_c = 1.1 \times (Q_1 + Q_2) \quad (\text{Eq. 8})$$

2.6.3. Energy production

The daily energy production (E_d) is given by:

$$E_d = Q_{CH4} \times Q_i \quad (\text{Eq. 9})$$

Thermal and electrical efficiency.

The thermal and electrical efficiency of the CHP engine is considered using the following equations.

a Thermal Efficiency:

$$N_t = \left(\frac{Q_{CH4}}{24} \right) \times Q_i \times \eta_t \quad (\text{Eq. 10})$$

where.

- N_t is the thermal energy output (MJ/day).
 - η_t is the thermal efficiency of the CHP engine (0.43).
- b Electrical Efficiency:

$$N_e = \left(\frac{Q_{CH4}}{24} \right) \times Q_i \times \eta_e \quad (\text{Eq. 11})$$

where.

- N_e is the electrical energy output (MJ/day).
- η_e is the electrical efficiency of the CHP engine (0.38).

2.6.4. Data used for calculations

Assumptions. for the calculations include a methane yield (Y_m) of $107.80 \text{ L CH}_4/\text{kg COD}$ (experimental result obtained from this study) and a total load (L) of 1000 kg COD/day . The temperatures were 45°C (318 K) for AD, 27.5°C (300.5 K) as the annual average air temperature in Kuwait, and 25°C (298 K) for the feedstock. The feedstock flow rate (Vos) was $10 \text{ m}^3/\text{day}$, and the digester (D) diameter was 5 m .

These data points were used to estimate energy and determine the feasibility and efficiency of the AD process for oily sludge treatment using a CHP system. The equations provided were applied to calculate the daily methane production, thermal energy potential, and energy demand, leading to a comprehensive analysis of the process's energy balance and feasibility.

3. Results and discussion

3.1. Physico-biochemical characterization of the sludge samples

Oily sludge exhibits significant variations in its physical qualities due to the heterogeneity of its chemical contents. Furthermore, the characteristics derived from one specific sludge source cannot be applied to those from a different source (Hu et al., 2013). Hence, physical-biochemical characterization has been done since it was crucial before AD (Table 2).

The high chemical oxygen demand (COD) values indicate the presence of significant organic matter in PS, suggesting a promising potential for biomethane production through AD. The COD/TS ratios also support the suitability of these substrates for the process. The TS contents are slightly higher than those found in literature, ranging from 100 to 600 g/kg TS (Jerez et al., 2021; Liu et al., 2012; Mohan and Chandrasekhar, 2011). The sludges' pH was in the neutral range with practically no variation. The HHV of the oily sludge was 3950 kcal/kg , almost similar to those found for a refinery oily sludge with an average value of 3700 kcal/kg (Jerez et al., 2021; Nazem and Tavakoli, 2017). The specific heat of the PS ranged from $2450 \text{ kJ/m}^3\cdot\text{K}$ to $2950 \text{ kJ/m}^3\cdot\text{K}$. This highlights the sludge's capacity for heat absorption, which is essential for maintaining stable temperatures during AD. This value will be used later in the energy estimation section. Such thermal properties are crucial for optimizing the digestion system's energy efficiency and overall performance.

3.2. Methane potential in batch reactors

3.2.1. Methane production at 37°C

As mentioned in the materials and methods section, all samples were tested in duplicate, following a Total Solids (TS) ratio in the digesters of $3/1$ (Inoculum/Substrate). This ratio was optimal for methane production from PS (Korai et al., 2024) and other types of waste, such as wastewater sludge (El Achkar et al., 2023).

The findings in Fig. 3A show significant trends in methane production among the various digesters over 60 days of AD at 37°C . The digesters with Inoculum + Petroleum Oily Sludge produced the highest amount of methane throughout the experiment. It started quickly and steadily increased, reaching 4.53 NL of methane by day 60. In contrast, the "Inoculum + Desalter Sludge" digesters produced almost the same amount of methane as the Inoculum Alone setup. The similarity suggests that the desalter sludge may contain components that inhibit the bacterial activity that produces methane. Factors in the desalter sludge, such as salts or other chemicals, could potentially interfere with microbial activity, reducing methane production.

The Inoculum Alone arrangement produced a continuous increase in methane, reaching around 3.58 L by the end of the 60 days. The significant difference in methane production between the digesters shows that the microbial population in the cow manure may be more successful at breaking down the organic compounds present in the petroleum oily sludge than the desalter sludge.

3.2.2. Methane production at 45°C

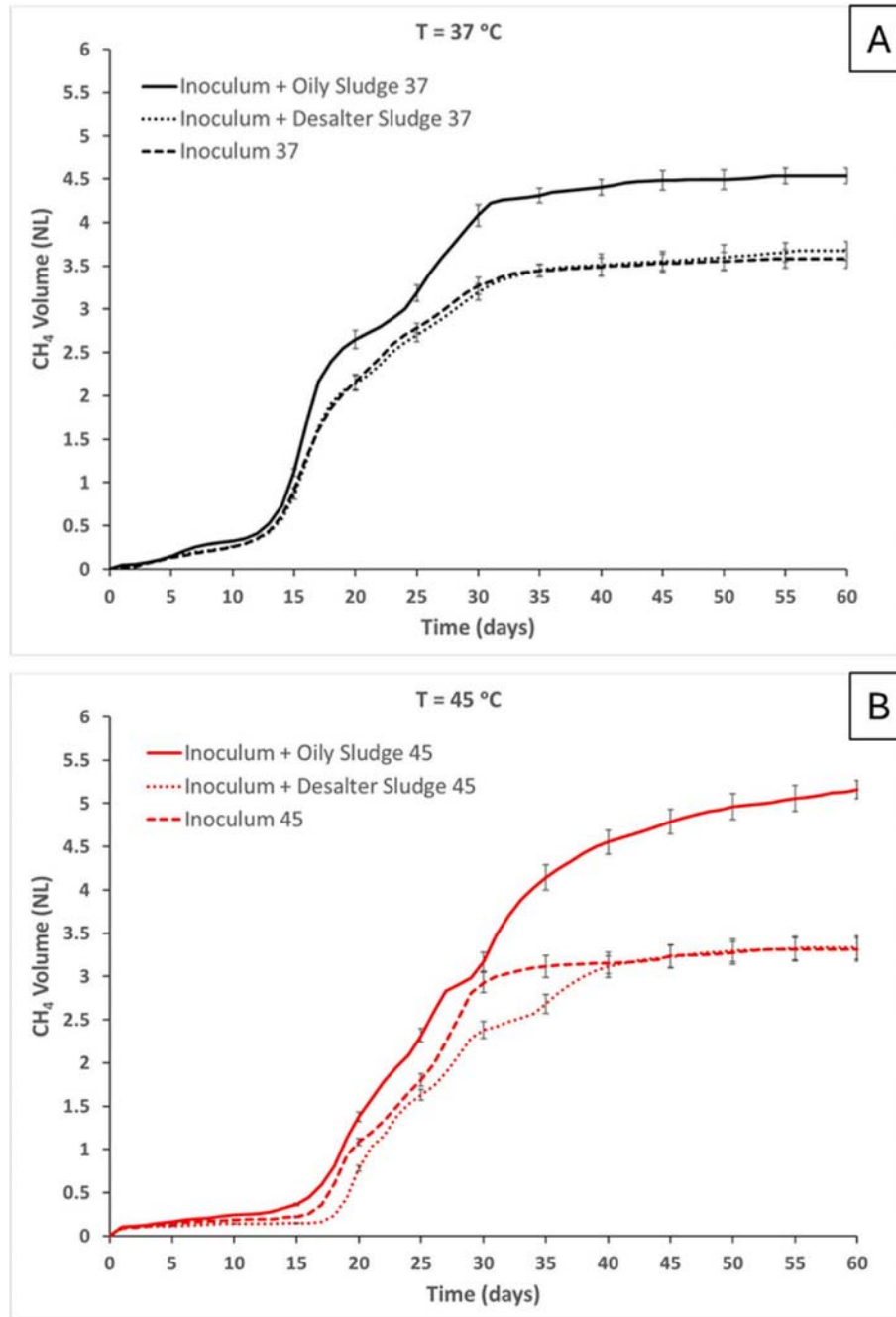
The study of methane production at 45°C reveals significant differences in gas yield across experimental setups compared to 37°C , as illustrated in Fig. 3B. At 45°C , all digesters produced more methane over 60 days than at 37°C . By Day 60, the Inoculum Alone digesters at 45°C had produced roughly 3.31 NL of methane, representing a 7.6% increase in gas production over the similar setup at 37°C .

Methane output for the "Inoculum + Desalter Sludge" digesters at 45°C reached roughly 3.33 NL by day 60, representing a 6.8% improvement over its performance at 37°C , indicating similar gas production trends between the two temperatures. As under 37°C , the desalter sludge showed no degradation or conversion to methane since the amount of gas recorded was almost similar to the inoculum alone.

Table 2

Components of petroleum sludge samples used in the experiments.

Substrate	COD (gO ₂ /kg)	TS (g/kg)	COD/TS	P (mg/kg)	N (mg/kg)	pH	HHV (kcal/kg)	Specific heat (kJ/m ³ K)
Oily Sludge	400 ± 25	695 ± 20	0.57	0.05	0.4	7.2	3950 ± 250	2950 ± 120
Desalter Sludge	340 ± 15	781 ± 10	0.43	0.06	0.6	7.0	3320 ± 180	2450 ± 130

**Fig. 3.** Cumulative methane production from the samples at 37 °C (A) and 45 °C (B). Bars represent the average standard deviation of the experimental data.

On the other hand, the "Inoculum + Petroleum Oily Sludge" digesters at 45 °C showed a significant increase, producing roughly 5.16 NL of methane by day 60. This result reflects a 35% increase in methane generation over the performance of the same setup at 37 °C.

When the percentage increase in gas production between the two temperatures is compared, the Inoculum + Petroleum Oily Sludge configuration has the most remarkable improvement. The combination

of methane volumes and percentage increase illustrates how temperature affects methane creation. The rise in gas output across all digesters at 45 °C indicates the positive effect of higher temperatures on methane production. However, the persisting issues associated with the desalter sludge are still visible even at higher temperatures.

The significant difference in methane production between the digesters indicates that the microbial population in the inoculum is more

effective at breaking down the organic compounds present in petroleum oily sludge than desalter sludge. This observation emphasizes the importance of understanding the composition of waste materials in AD processes.

Several factors could explain the reduced methane production observed with desalter sludge.

- **High Salt Content:** Desalter sludge often contains high levels of salts, which can have inhibitory effects on methanogenic bacteria (Li et al., 2023). High salt concentrations can lead to osmotic stress, reducing microbial activity and methane production. Salts can also precipitate essential nutrients, making them unavailable to microbes.
- **Presence of Inhibitory Chemicals:** Desalter sludge may contain various chemicals used in the desalting process, such as demulsifiers, corrosion inhibitors, and other treatment chemicals. These substances can be toxic to anaerobic microbes, further inhibiting their activity and methane production (Chen et al., 2014).
- **Reduced Biodegradability:** The organic matter in desalter sludge might be less biodegradable than in petroleum oily sludge. Complex hydrocarbons and other refractory compounds in desalter sludge may not be as readily broken down by the microbial community, leading to lower methane yields.
- **Microbial Community Dynamics:** The microbial community composition in the inoculum might be more suited to degrade the organic compounds in petroleum oily sludge than those in desalter sludge. The presence of specific microbial populations that are more effective at breaking down specific substrates can significantly impact methane production.

Further research on the inhibitory components in desalter sludge is required to optimize AD methods for PS treatment. Understanding these obstacles can help refine the process and identify appropriate waste sources for efficient methane production via AD. Addressing the challenges of desalter sludge could lead to more effective treatment strategies and improved biogas yields.

3.3. Kinetics study and anaerobic biodegradability

To evaluate the anaerobic biodegradability of oily sludge, the methane production volumes from the "Petroleum Oily Sludge" digesters were first corrected by subtracting the methane production volumes from the Inoculum alone setup. The corrected data were then divided by the amount of COD present in the sample, which was determined to be 400 g COD per kg of oily sludge. To determine the biodegradability, the highest methane production obtained was divided by 350 using the formula described in the materials and methods section. Fig. 4 illustrates the experimental and modeled curves based on these calculations.

The experimental results and kinetic parameters obtained from the Modified Gompertz Model are summarized in Table 3. The model's correlation coefficients (R^2) were 0.988 for 37 °C and 0.997 for 45 °C, indicating an excellent fit of the Modified Gompertz Model to the experimental data. The experimental methane yield for oily sludge at 37 °C was 67.8 NL/kg COD, while at 45 °C, it was 135.0 NL/kg COD. This indicates a significant increase in methane production at the higher temperature, reflecting enhanced biodegradation.

The Modified Gompertz Model predicted methane yields of 69.8 NL/kg COD for 37 °C and 154.0 NL/kg COD for 45 °C. The differences between experimental and predicted yields were 3.0% and 14.0%, respectively, indicating a good fit of the model to the experimental data.

Table 3

Kinetic parameters and biodegradability of oily sludge at 37 °C and 45 °C.

Parameter	Oily Sludge 37 °C	Oily Sludge 45 °C
Experimental methane yield (NL/kg COD)	67.8	135.0
Predicted methane yield, P (NL/kg COD)	69.8	154.0
Difference between experimental and predicted gas yield (%)	3.0	14.0
Maximum methane production rate, R (NL/kg COD/day)	3.24	3.96
Residence time, λ (days)	12.4	15.4
Correlation coefficient, R^2	0.988	0.997
Experimental Biodegradability (%)	19.4	38.6
Predicted Biodegradability (%)	19.9	44.0

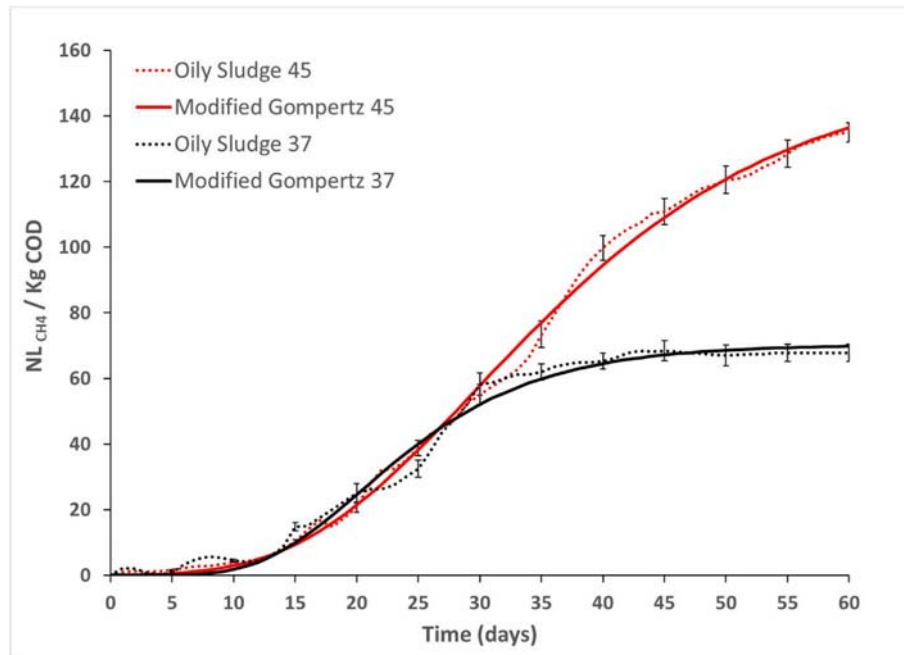


Fig. 4. Experimental and Predicted methane production (NL/Kg_{COD}) from Oily sludge samples at 37 °C and 45 °C. Bars represent the average standard deviation of the experimental data.

The maximum methane production rate (R) increased from 3.24 NL/kg COD/day at 37 °C to 3.96 NL/kg COD/day at 45 °C. This increase suggests that microbial activity and substrate conversion were more efficient at the higher temperature.

The lag phase increased from 12.4 days at 37 °C to 15.4 days at 45 °C, likely due to the initial adaptation period required by the microbial community to acclimatize to the elevated temperature. Those extended lag phase periods can be attributed to several factors. Firstly, using cow manure as the inoculum, rather than anaerobic inoculum from established anaerobic digesters, contributed to the more prolonged lag phase. In Kuwait, the non-availability of specialized anaerobic inoculum necessitated cow manure, which required additional time to adapt to the specific temperature conditions and the complex nature of the oily sludge. Secondly, the complexity of the waste itself plays a significant role. PS is a challenging substrate for AD due to its intricate composition, including various hydrocarbons and other refractory compounds. The anaerobic bacteria needed time to acclimate and establish a stable microbial community capable of efficiently degrading such complex organic matter. Overall, using cow manure as the inoculum and dealing with a complex waste substrate likely contributed to the high lag phases observed in the experiments.

The experimental biodegradability of the oily sludge from the experiments at 37 °C was found to be 19.4%, while at 45 °C, it increased to 38.6%. Considering the model-predicted methane yield, the biodegradability of the oily sludge at 37 °C was found to be 19.9%, while at 45 °C, it increased to 44.0%. The significant increase in biodegradability reported at 45 °C highlights the primary influence of increased temperatures on oily sludge biodegradation. These results are important as they reflect a previously unreported level of efficacy in the literature. Considering its complex composition and limited exploitation, achieving up to 44% biodegradation of PS is noteworthy.

Compared to other substrates, such as grape pomace, where anaerobic biodegradability of total COD ranges from 30% to 69% (El Achkar et al., 2017), reaching 40% with PS is notable. This demonstrates again the potential for AD of PS as a viable waste management and energy recovery strategy. Future studies could assess the effects of pre-treatments to increase the biodegradability of PS, potentially enhancing the AD process and improving energy recovery (El Achkar et al., 2018c).

The results demonstrate that increasing the temperature from 37 °C

to 45 °C significantly enhances oily sludge's biodegradation and methane production potential. The higher biodegradability and methane yield at 45 °C can be attributed to the accelerated microbial metabolism and enzymatic activities at elevated temperatures, which facilitate the breakdown of complex organic compounds in the sludge.

3.4. Methane production in continuous reactors

Since the highest methane yields and biodegradation rates were obtained at 45 °C, continuous AD experiments were conducted using oily sludge at that temperature, with the system operating over 120 days. Continuous reactors are critical for assessing the long-term stability and efficiency of the process. They allow for the monitoring of steady-state conditions and provide insights into the operational challenges and performance of the system under sustained loading. The methane production data, expressed as NL CH₄ per kg COD per day, is presented in Fig. 5, along with the TVA/Alkalinity ratio. This data is essential for understanding digestion's behavior and evaluating methane production's overall efficacy.

As depicted in Fig. 5, during the initial start-up period, the OLR was gradually increased to allow the microbial community to acclimatize to the oily sludge. The OLR was incremented from 0.5 Kg COD/m³/day (7 days) to 1.0 Kg COD/m³/day (7 days), then to 1.5 Kg COD/m³/day (7 days), 2.0 Kg COD/m³/day (7 days), and finally to 2.5 Kg COD/m³/day. After reaching this OLR, digesters underwent a 90-day operational period, equivalent to thrice the HRT, ensuring that the system reached a stable state, marked by consistent gas production.

Stable Production Phase (28–120 Days): From day 28 onwards, methane production increased steadily, reaching a peak of 108 NL CH₄/Kg COD/day by day 95. The system achieved consistent methane production, indicating that it had reached a stable state. After day 95, the methane production remained relatively stable, fluctuating slightly around 105–108 NL CH₄/Kg COD/day.

The maximum methane production rate observed was around 108 NL CH₄/Kg COD/day on days 95, 110, and 120, demonstrating the effectiveness of the continuous system in converting oily sludge into methane.

The TVA/Alkalinity ratio is critical for monitoring process stability in anaerobic digesters. A ratio of less than 0.4 is recommended for stable

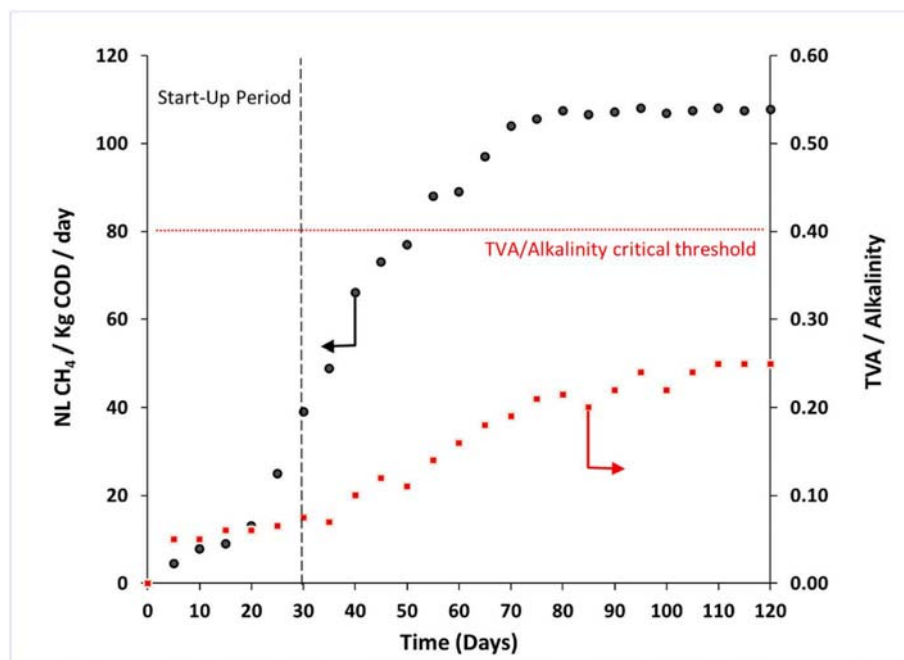


Fig. 5. Methane Production and TVA/Alkalinity Ratio in Continuous Reactors under 45 °C. Values correspond to the mean of the measurement.

operation (Callaghan et al., 2002). Fig. 5 indicates that the TVA/Alkalinity ratio remained below 0.25 throughout the 120 days, suggesting stable digestion conditions. The experiment's relatively low and stable TVA/Alkalinity ratio indicates that the reactor maintained good process stability. The highest ratio observed was 0.25, well below the threshold of 0.4, indicating that excessive volatile acids did not inhibit the process. In addition, the pH values remained within a suitable range (6.8–7.2), further confirming the stability of the AD process.

The stable methane production and low TVA/Alkalinity ratios observed over the 120 days indicate that the process can be reliably scaled up to larger systems without significant fluctuations in performance.

On another note, no foaming was observed during the continuous reactor experiments, a positive indicator of process stability. The absence of foaming suggests that the AD process was well-controlled, with a balanced organic loading rate, optimal microbial populations, and stable pH levels.

To proceed with a technical evaluation of the digester, the methane production efficiency from oily sludge was assessed by comparing batch and continuous modes. Methane production in the continuous pilot represented 80% of that obtained in the batch system, aligning with efficiencies reported in the literature, which range between 75% and 90% (El Achkar et al., 2016; Kafle and Kim, 2013; Sambusiti et al., 2013). Several factors in this study could explain the slight discrepancy in efficiency between the batch and continuous experiments.

In the batch system, the PS and microorganisms have a longer contact time, which allows for more complete degradation of the substrates. The extended exposure time enhances microbial activity and substrate breakdown, producing higher methane yields.

The difference in residence time distribution between batch and continuous systems can impact the efficiency of substrate degradation. In a batch system, all the substrate remains in the reactor for the entire experiment. In contrast, new substrate is continuously added in a continuous system, and digestate is removed, leading to a variation in residence time and potentially less complete degradation.

Finally, the mixing systems in batch and continuous reactors can also

affect the degradation efficiency. The batch system mixes the contents periodically, ensuring a uniform distribution of microorganisms and substrates. In contrast, continuous systems may experience variations in mixing efficiency, potentially leading to localized areas of lower microbial activity and reduced substrate degradation.

3.5. Energy estimation

The energy estimation analysis for the AD process and CHP system was conducted to assess the potential energy production and feasibility. The results obtained from the methane production data and subsequent calculations are summarized in Fig. 6. This diagram visualizes the energy flow, showing the theoretical thermal energy production from methane, the energy demands for heating and heat loss, and the net energy production available.

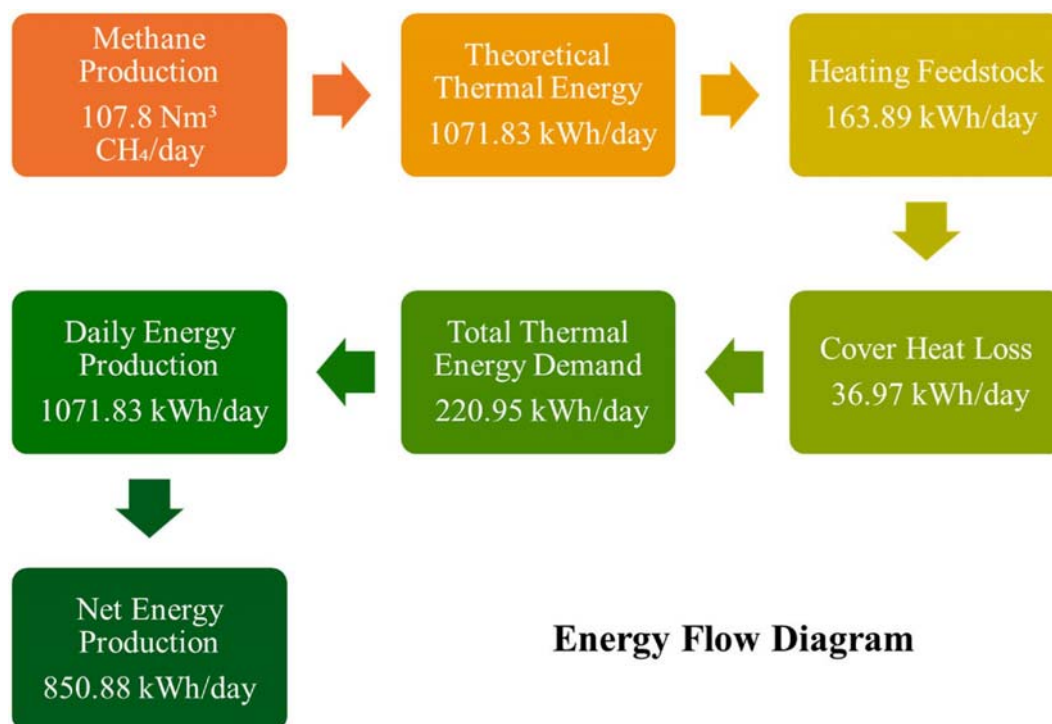
The energy estimation results demonstrate the AD process's feasibility and efficiency for oily sludge treatment using a CHP system. The significant daily methane production and net positive energy output are key indicators of the process's effectiveness.

The daily methane production of $107.8 \text{ Nm}^3 \text{ CH}_4/\text{day}$ highlights the high potential for converting oily sludge into valuable methane. The theoretical thermal energy of 3859.24 MJ/day (or 1071.83 kWh/day) provides substantial energy that can be harnessed for electricity generation and heating. The total thermal energy demand, including the energy required for heating the feedstock and covering heat loss, was calculated to be $795,421 \text{ kJ/day}$ (220.95 kWh/day). This indicates the energy required to maintain the digester's operational conditions.

The process demonstrates a positive energy balance with a net energy production of 850.88 kWh/day , confirming its feasibility and efficiency. This surplus energy can offset operational costs or be sold back to the grid, providing economic benefits.

The thermal efficiency of 68.61 MJ/day and electrical efficiency of 61.02 MJ/day indicate that a significant portion of the energy content in the biogas is effectively converted to valuable energy. These efficiencies contribute to the overall feasibility and attractiveness of the process.

Optimizing methane production by modifying the temperature in AD



Energy Flow Diagram

Fig. 6. Energy flow and net energy production from anaerobic digestion of petroleum sludge.

processes is crucial. Studies comparing several temperatures indicate that higher temperatures can enhance biogas production, balancing the additional energy needed for heating (Andersson et al., 2020). Utilizing excess thermal energy from biogas through a CHP system is economical to maintain optimal temperatures, though its thermal efficiency is typically limited to around 40–45% (Deng et al., 2014; Kougiyas and Angelidaki, 2018).

Therefore, using excess thermal energy from biogas via a CHP system increases the overall energy efficiency of the process. Capturing and utilizing the thermal energy generated during biogas production minimizes energy losses and maximizes resource utilization. Economic feasibility and practical implementation of the CHP method must be considered, including factors like energy conversion efficiency, infrastructure requirements, and operational costs.

Methane from AD as a fuel for CHP systems is a renewable energy source, reducing dependence on fossil fuels and enhancing energy sustainability. Capturing and utilizing methane from AD prevents its release into the atmosphere, providing significant environmental benefits. Additionally, the positive net energy production highlights the economic viability of the process, with surplus energy offsetting facility energy costs or providing additional revenue.

4. Conclusion

This study investigated the anaerobic digestion (AD) of petroleum sludge (PS) for bioenergy production, focusing on oily and desalter sludge from local industries in Kuwait. The anaerobic biodegradability of oily sludge improved significantly at 45 °C, increasing from 19.9% at 37 °C to 44.0% at 45 °C. Batch reactor studies revealed that the "Inoculum + Petroleum Oily Sludge" setup produced the maximum methane yield, particularly at 45 °C, confirming the beneficial effects of higher temperatures. Continuous digestion tests at 45 °C yielded stable methane generation and low TVA/Alkalinity ratios for the process scale-up, indicating high stability. The continuous reactor achieved 80% of the batch system's methane generation efficiency, likely due to extended contact time and residence time distribution in batch mode. The theoretical thermal energy from methane combustion was 1071.83 kWh/day, with a net energy output of 850.88 kWh/day, demonstrating the economic and environmental viability of the anaerobic digestion process when combined with a CHP system for oily sludge treatment.

Future research should investigate pretreatment approaches to improve the biodegradability of PS and use specific anaerobic inoculum to shorten the lag phase and increase efficiency. The promising results suggest that the process can be scaled up to industrial levels, although thorough economic and feasibility studies are required. Quantifying environmental benefits using life cycle analysis can provide detailed insights into the process's sustainability. In conclusion, this study shows that AD can treat PS while creating sustainable energy. The findings provide a solid platform for future research and development to implement sustainable waste management strategies in the petroleum industry while moving towards net-zero emissions and carbon-neutral operations.

CRedit authorship contribution statement

Jean H. El Achkar: Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rana Malhas:** Writing – review & editing, Visualization, Formal analysis, Data curation. **Faisal Albalool:** Validation, Resources, Investigation. **Abdullah Alrabaie:** Validation, Resources, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

the work reported in this paper.

Acknowledgment

The authors would like to thank the Australian University in Kuwait for supporting this research and the individuals who supplied sludge and manure samples.

Data availability

Data will be made available on request.

References

- American Public Health Association, Eaton, A.D., 2005. American water works association, water environment federation. Stand. Methods Exam. Water Wastewater 2–3. APHA-AWWA-WEF, Washington, D.C., 23rd Edition. Volume (Part 2540 B).
- Ampese, L.C., Sganzerla, W.G., Di Domenico Ziero, H., Mudhoo, A., Martins, G., Forster-Carneiro, T., 2022. Research progress, trends, and updates on anaerobic digestion technology: a bibliometric analysis. *J. Clean. Prod.* 331, 130004. <https://doi.org/10.1016/j.jclepro.2021.130004>.
- Andersson, J., Helander-Claesson, J., Olsson, J., 2020. Study on reduced process temperature for energy optimisation in mesophilic digestion: a lab to full-scale study. *Appl. Energy* 271, 115108. <https://doi.org/10.1016/j.apenergy.2020.115108>.
- Brauer, H.B., Khan, J., 2021. Diffusion of Biogas for Freight Transport in Sweden: A User Perspective 127738.
- Buffiere, P., Frederic, S., Marty, B., Delgenes, J.-P., 2008. A comprehensive method for organic matter characterization in solid wastes in view of assessing their anaerobic biodegradability. *Water Sci. Technol. J. Int. Assoc. Water Pollut. Res.* 58, 1783–1788. <https://doi.org/10.2166/wst.2008.517>.
- Callaghan, F.J., Wase, D.A.J., Thayani, K., Forster, C.F., 2002. Continuous co-digestion of cattle slurry with fruit and vegetable wastes and chicken manure. *Biomass Bioenergy* 22, 71–77. [https://doi.org/10.1016/S0961-9534\(01\)00057-5](https://doi.org/10.1016/S0961-9534(01)00057-5).
- Chen, J.L., Ortiz, R., Steele, T.W.J., Stuckey, D.C., 2014. Toxicants inhibiting anaerobic digestion: a review. *Biotechnol. Adv.* 32, 1523–1534. <https://doi.org/10.1016/j.biotechadv.2014.10.005>.
- Chen, Y.-C., 2018. Evaluating greenhouse gas emissions and energy recovery from municipal and industrial solid waste using waste-to-energy technology. *J. Clean. Prod.* 192, 262–269. <https://doi.org/10.1016/j.jclepro.2018.04.260>.
- Deng, L., Yang, H., Liu, G., Zheng, D., Chen, Z., Liu, Y., Pu, X., Song, L., Wang, Z., Lei, Y., 2014. Kinetics of temperature effects and its significance to the heating strategy for anaerobic digestion of swine wastewater. *Appl. Energy* 134, 349–355. <https://doi.org/10.1016/j.apenergy.2014.08.027>.
- El Achkar, J., 2017. Méthanisation de marc de raisin. Caractérisation et optimisation du procédé et des prétraitements (These de doctorat). Lorient.
- El Achkar, J.H., 2022. Sustainable solid waste management: towards a complete and effective strategy. *Arab J. STI Policies* 3, 9–17. <https://doi.org/10.21608/ARABSTI.2023.291066>.
- El Achkar, J.H., Baydoun, A., Salameh, D., Louka, N., Hobaika, Z., Maroun, R.G., 2018a. Can coffee grounds be considered as a potential for green energy production?. In: 2018 4th International Conference on Renewable Energies for Developing Countries (REDEC). Presented at the 2018 4th International Conference on Renewable Energies for Developing Countries (REDEC), pp. 1–6. <https://doi.org/10.1109/REDEC.2018.8598105>.
- El Achkar, J.H., El Joahuri, A., Nassreddine, C., Mgharbel, M., Izmerly, Y., 2023. Anaerobic digestion of wastewater sludge for improved energy recovery: alkaline pretreatment impact, digestate quality assessment, and reactor design. *Arabian J. Sci. Eng.* <https://doi.org/10.1007/s13369-023-08068-1>.
- El Achkar, J.H., Husain, A.B., Alotaibi, N., Alhaddad, N., Alamgir, T., Alshamali, H., Alshammari, Y., Almuhamma, M., Albekheet, A., Alenezi, K., Alsaba, M.T., 2022. Could petroleum sludge be used to produce biomethane as a renewable energy source? Presented at the ADIPEC. OnePetro. <https://doi.org/10.2118/210953-MS>.
- El Achkar, J.H., Lendormi, T., Hobaika, Z., Salameh, D., Louka, N., Maroun, R.G., Lanoisellé, J.-L., 2017. Anaerobic digestion of nine varieties of grape pomace: correlation between biochemical composition and methane production. *Biomass Bioenergy* 107, 335–344. <https://doi.org/10.1016/j.biombioe.2017.10.030>.
- El Achkar, J.H., Lendormi, T., Hobaika, Z., Salameh, D., Louka, N., Maroun, R.G., Lanoisellé, J.-L., 2016. Anaerobic digestion of grape pomace: biochemical characterization of the fractions and methane production in batch and continuous digesters. *Waste Manag.* 50, 275–282. <https://doi.org/10.1016/j.wasman.2016.02.028>.
- El Achkar, J.H., Lendormi, T., Salameh, D., Louka, N., Maroun, R.G., Lanoisellé, J.-L., Hobaika, Z., 2018b. Anaerobic digestion of grape pomace: effect of the hydraulic retention time on process performance and fibers degradability. *Waste Manag.* 71, 137–146. <https://doi.org/10.1016/j.wasman.2017.11.005>.
- El Achkar, J.H., Lendormi, T., Salameh, D., Louka, N., Maroun, R.G., Lanoisellé, J.-L., Hobaika, Z., 2018c. Influence of pretreatment conditions on lignocellulosic fractions and methane production from grape pomace. *Bioresour. Technol.* 247, 881–889. <https://doi.org/10.1016/j.biortech.2017.09.182>.
- El Achkar, J.H., Rohayem, C., Salameh, D., Louka, N., Maroun, R.G., Hobaika, Z., 2018d. Olive pomace, a source of green energy using anaerobic digestion. In: 2018 4th International Conference on Renewable Energies for Developing Countries (REDEC).

- Presented at the 2018 4th International Conference on Renewable Energies for Developing Countries (REDEC), pp. 1–6. <https://doi.org/10.1109/REDEC.2018.8598079>.
- El Achkar, J.H., Ziade, R., Louka, N., Maroun, R.G., Hobaiika, Z., 2020. Treatment of dairy waste by anaerobic digestion to produce methane as green energy. In: 2020 5th International Conference on Renewable Energies for Developing Countries (REDEC). Presented at the 2020 5th International Conference on Renewable Energies for Developing Countries (REDEC), pp. 1–6. <https://doi.org/10.1109/REDEC49234.2020.9163848>.
- Ezemagu, I.G., Ejimofor, M.I., Menkiti, M.C., 2020. Thermodynamic studies of anaerobic digestion of post coagulation sludge from petroleum produced water and cow dung. *Curr. Res. Green Sustain. Chem.* 3, 100037. <https://doi.org/10.1016/j.crgsc.2020.100037>.
- Haak, L., Roy, R., Pagilla, K., 2016. Toxicity and biogas production potential of refinery waste sludge for anaerobic digestion. *Chemosphere* 144, 1170–1176. <https://doi.org/10.1016/j.chemosphere.2015.09.099>.
- Hakawati, R., Smyth, B.M., McCullough, G., De Rosa, F., Rooney, D., 2017. What is the most energy efficient route for biogas utilization: heat, electricity or transport? *Appl. Energy* 206, 1076–1087. <https://doi.org/10.1016/j.apenergy.2017.08.068>.
- Hu, G., Li, J., Zeng, G., 2013. Recent development in the treatment of oily sludge from petroleum industry: a review. *J. Hazard. Mater.* 261, 470–490. <https://doi.org/10.1016/j.jhazmat.2013.07.069>.
- Janajreh, I., Alshehi, A., Elagroudy, S., 2020. Anaerobic co-digestion of petroleum hydrocarbon waste and wastewater treatment sludge. *Int. J. Hydrogen Energy* 45, 11538–11549. <https://doi.org/10.1016/j.ijhydene.2018.05.100>.
- Jerez, S., Ventura, M., Molina, R., Pariente, M.I., Martínez, F., Melero, J.A., 2021. Comprehensive characterization of an oily sludge from a petrol refinery: a step forward for its valorization within the circular economy strategy. *J. Environ. Manag.* 285, 112124. <https://doi.org/10.1016/j.jenvman.2021.112124>.
- Johnson, O.A., Affam, A.C., 2019. Petroleum sludge treatment and disposal: a review. *Environ. Eng. Res.* 24, 191–201. <https://doi.org/10.4491/eer.2018.134>.
- K, B., Pilli, S., Rao, P.V., Tyagi, R.D., 2024. Predictive modelling of methane yield in biochar-amended cheese whey and septage co-digestion: exploring synergistic effects using Gompertz and neural networks. *Chemosphere* 353, 141558. <https://doi.org/10.1016/j.chemosphere.2024.141558>.
- Kafle, G.K., Kim, S.H., 2013. Anaerobic treatment of apple waste with swine manure for biogas production: batch and continuous operation. *Appl. Energy* 103, 61–72. <https://doi.org/10.1016/j.apenergy.2012.10.018>.
- Kankia, M.U., Baloo, L., Danlami, N., Mohammed, B.S., Haruna, S., Abubakar, M., Jagaba, A.H., Sayed, K., Abdulkadir, I., Salihi, I.U., 2021. Performance of fly ash-based inorganic polymer mortar with petroleum sludge ash. *Polymers* 13, 4143. <https://doi.org/10.3390/polym13234143>.
- Kardena, Q.H.E., 2015. Petroleum oil and gas industry waste treatment; common practice in Indonesia. *J. Pet. Environ. Eng.* <https://doi.org/10.4172/2157-7463.1000241>, 2015.
- Klenert, D., Funke, F., Mattauch, L., O'Callaghan, B., 2020. Five lessons from COVID-19 for advancing climate change mitigation. *Environ. Resour. Econ.* 76, 751–778. <https://doi.org/10.1007/s10640-020-00453-w>.
- Korai, M.S., Pinjaro, M.A., Bhatti, Z.A., Herrapstanti, E.H., Jatoi, M., Shar, M.A., Alhazaa, A., 2024. Co-digestion of petroleum sludge and Buffalo dung by batch anaerobic digestion system. *J. Ecol. Eng.* 25, 120–127. <https://doi.org/10.12911/22998993/186898>.
- Kougias, P.G., Angelidaki, I., 2018. Biogas and its opportunities—a review. *Front. Environ. Sci. Eng.* 12, 14. <https://doi.org/10.1007/s11783-018-1037-8>.
- Kunatsa, T., Xia, X., 2022. A review on anaerobic digestion with focus on the role of biomass co-digestion, modelling and optimisation on biogas production and enhancement. *Bioresour. Technol.* 344, 126311. <https://doi.org/10.1016/j.biortech.2021.126311>.
- Li, J., Xu, X., Chen, C., Xu, L., Du, Z., Gu, L., Xiang, P., Shi, D., Huangfu, X., Liu, F., 2023. Conductive materials enhance microbial salt-tolerance in anaerobic digestion of food waste: microbial response and metagenomics analysis. *Environ. Res.* 227, 115779. <https://doi.org/10.1016/j.envres.2023.115779>.
- Liu, W., Wang, X., Wu, L., Chen, M., Tu, C., Luo, Y., Christie, P., 2012. Isolation, identification and characterization of *Bacillus amyloliquefaciens* BZ-6, a bacterial isolate for enhancing oil recovery from oily sludge. *Chemosphere* 87, 1105–1110. <https://doi.org/10.1016/j.chemosphere.2012.01.059>.
- Mohan, S.V., Chandrasekhar, K., 2011. Self-induced bio-potential and graphite electron accepting conditions enhances petroleum sludge degradation in bio-electrochemical system with simultaneous power generation. *Bioresour. Technol.* 102, 9532–9541. <https://doi.org/10.1016/j.biortech.2011.07.038>.
- Murungi, P.I., Sulaimon, A.A., 2022. Petroleum sludge treatment and disposal techniques: a review. *Environ. Sci. Pollut. Res.* 29, 40358–40372. <https://doi.org/10.1007/s11356-022-19614-z>.
- Nazem, M.A., Tavakoli, O., 2017. Bio-oil production from refinery oily sludge using hydrothermal liquefaction technology. *J. Supercrit. Fluids* 127, 33–40. <https://doi.org/10.1016/j.supflu.2017.03.020>.
- Paul Choudhury, S., Saha, B., Haq, I., Kalamdhad, A.S., 2022. 17 - use of petroleum refinery sludge for the production of biogas as an alternative energy source: a review. In: Hussain, C., Hait, S. (Eds.), *Advanced Organic Waste Management*. Elsevier, pp. 277–297. <https://doi.org/10.1016/B978-0-323-85792-5.00021-6>.
- Ritchie, H., Roser, M., 2020. CO₂ and Greenhouse Gas Emissions. Our World Data.
- Roy, R., Haak, L., Li, L., Pagilla, K., 2016. Anaerobic digestion for solids reduction and detoxification of refinery waste streams. *Process Biochem.* 51, 1552–1560. <https://doi.org/10.1016/j.procbio.2016.08.006>.
- Sambusiti, C., Ficarra, E., Malpei, F., Steyer, J.P., Carrère, H., 2013. Benefit of sodium hydroxide pretreatment of ensiled sorghum forage on the anaerobic reactor stability and methane production. *Bioresour. Technol.* 144, 149–155. <https://doi.org/10.1016/j.biortech.2013.06.095>.
- Szaja, A., Montusiewicz, A., 2019. Enhancing the co-digestion efficiency of sewage sludge and cheese whey using brewery spent grain as an additional substrate. *Bioresour. Technol.* 291, 121863. <https://doi.org/10.1016/j.biortech.2019.121863>.
- Szaja, A., Montusiewicz, A., Lebioccka, M., 2021. The energetic aspect of organic wastes addition on sewage sludge anaerobic digestion: a laboratory investigation. *Energies* 14, 6113. <https://doi.org/10.3390/en14196113>.
- Van, D.P., Fujiwara, T., Tho, B.L., Toan, P.P.S., Minh, G.H., 2020. A review of anaerobic digestion systems for biodegradable waste: configurations, operating parameters, and current trends. *Environ. Eng. Res.* 25, 1–17. <https://doi.org/10.4491/eer.2018.334>.
- Wang, Q., Liang, Y., Zhao, P., Li, Q.X., Guo, S., Chen, C., 2016. Potential and optimization of two-phase anaerobic digestion of oil refinery waste activated sludge and microbial community study. *Sci. Rep.* 6, 38245. <https://doi.org/10.1038/srep38245>.
- Yaashikaa, P.R., Kumar, P.S., Saravanan, A., Varjani, S., Ramamurthy, R., 2020. Bioconversion of municipal solid waste into bio-based products: a review on valorisation and sustainable approach for circular bioeconomy. *Sci. Total Environ.* 748, 141312. <https://doi.org/10.1016/j.scitotenv.2020.141312>.
- Zamri, M.F.M.A., Hasnady, S., Akhiar, A., Ideris, F., Shamsuddin, A.H., Mofijur, M., Fattah, I.M.R., Mahlia, T.M.I., 2021. A comprehensive review on anaerobic digestion of organic fraction of municipal solid waste. *Renew. Sustain. Energy Rev.* 137, 110637. <https://doi.org/10.1016/j.rser.2020.110637>.



Utilizing eco-friendly shredded waste tires for oil spill cleanup: Adsorption isotherm and kinetic studies

Rana Malhas^{*,1}, Sara Salah, Mariam Alawadhi

Petroleum Engineering Department, College of Engineering, Australian University, PO Box: 1411, Safat 13015, Kuwait

ARTICLE INFO

Keywords:

Oil spill cleanup
Shredded waste tires
Adsorption
Kinetics
Isotherms

ABSTRACT

Oil spills present a significant environmental challenge, requiring effective and sustainable remediation strategies. The global generation of waste tires, which can have detrimental environmental effects when burned, necessitates innovative recycling methods. Recycling rubber reduces the demand for new raw materials, conserves natural resources, and lowers greenhouse gas emissions. This study explores using shredded waste tires (including powder, fiber, 0.5–2 mm and 2.5–3.5 mm granules, and Tire-derived fuel) as adsorbents for oil spill cleanup. Shredded tire particles, with their large surface area, porosity, hydrophobicity, and durability, are highly effective in oil adsorption. Optimal oil removal was achieved using a 2 g adsorbent dose, an initial oil concentration of 40 g/L, a 30-minute shaking time, a pH of 7, and a temperature of 25°C. Tire powders demonstrated exceptional efficiency, achieving an oil removal rate of 98.1 %. The adsorbent's high reusability, maintaining a 70.1 % oil removal percentage after 20 cycles, underscores its cost-effectiveness and environmental benefits. Batch adsorption experiments indicated that the process follows second-order kinetics and fits the Freundlich isotherm model. The maximum adsorption capacity was 15.44 g/g. This study highlights the potential of repurposing waste tires as a sustainable solution for mitigating oil spill contamination, offering dual benefits of waste management and environmental remediation.

1. Introduction

Oil spills occur when liquid petroleum or its byproducts are released into the environment, often contaminating bodies of water due to accidents, leaks, or human error. These incidents stem from various sources, including ships, pipelines, drilling rigs, and storage facilities [39]. Oil spill pollution is a major global concern, posing severe threats to ecosystems, wildlife, and human activities [11]. Historical disasters, such as the 1967 Torrey Canyon spill, which caused the deaths of 25,000 birds, and the 2010 BP Gulf of Mexico spill, which killed 997 birds, 400 sea turtles, and 47 mammals, highlight the devastating impact of such events [58]. Beyond immediate wildlife losses, oil spills disrupt ecosystems by causing oxidative damage to biomolecules, reducing oceanic plant life, and impairing food chains [40]. The contamination of water and land from oil spills and oily wastewater discharge further exacerbates environmental degradation, underscoring the urgency of effective spill management and mitigation strategies [11].

Efforts to mitigate oil spills have driven the development of various cleanup methods. Traditional approaches include the use of expanded

graphite, chalk, burning with wicking agents, detergents, floating barriers, polymeric foams, and enhanced biodegradation [2].

While effective to some extent, these techniques often involve high costs, limited efficiency, and potential environmental risks [14]. Advances in oil recovery technologies, such as biological treatments, membrane filtration, and sorbents derived from natural or synthetic materials, have also shown promise but face challenges related to reusability and post-treatment expenses [20,34,39], efforts [15].

Given the drawbacks of conventional methods, researchers have explored alternative materials for oil spill cleanup. Recycled rubber, particularly from shredded tires, has emerged as a promising option due to its natural oil-absorbing and hydrophobic properties [5]. Waste tires, primarily composed of vulcanized rubber reinforced with carbon black, exhibit characteristics akin to activated carbon, making them effective adsorbents for oil and organic compounds. Studies have demonstrated the reusability and efficiency of shredded tire powder for oil adsorption, positioning it as a sustainable and cost-effective solution [13,30]. Presently, the application of natural and synthetic sorbents for oil spill cleanup is widely employed due to their effectiveness, speed, and cost efficiency in mitigating environmental impacts [62]. Moreover,

* Corresponding author.

E-mail addresses: r.malhas@au.edu.kw (R. Malhas), 222200120@au.edu.kw (S. Salah), 222200194@au.edu.kw (M. Alawadhi).

¹ ORCID: 0000-0001-8070-8911.

Nomenclature

Ci	initial oil concentration of residue oil, g/L
Ce	crude oil concentration at equilibrium, g/L
M	mass of adsorbent, g
Min	minutes
T	Time
qe	adsorption density at equilibrium solute concentration, (g/g)
qm	maximum adsorption capacity of the adsorbent, (g/g)
qt	amount of adsorption at time t, (g/g)
K1	rate constant of pseudo first-order adsorption, min ⁻¹
K2	rate constant of pseudo second-order adsorption, (g/g/min)
K _F	Freundlich constant related to adsorption capacity (g/g) (L/g) ^{1/n}
K _L	Langmuir constant (L/g)
n	Freundlich constant related to adsorption intensity
R ²	correlation coefficient
R _L	separation factor, dimensionless constant t time taken for adsorption,
V	sample volume, L
TDF	Tire-derived fuel
API	American Petroleum Institute.

numerous studies have focused on utilizing natural adsorbents for removing petroleum oils, including crude oil [43,63].

Petroleum spills are recognized as one of the primary aquatic catastrophes responsible for the devastation and deterioration of marine ecosystems globally, causing the loss of thousands of organisms in a brief period [11]. Some of the factors contributing to this phenomenon may be associated with waste products from plastics and rubber tires [47]. Researchers are continually discovering new methods to recycle car tires to lessen their environmental impact [17,54,59].

Kuwait, facing a significant surge in tire waste, offers a compelling case for utilizing shredded tires in oil spill remediation. With an estimated 42 million tires previously dumped in desert graveyards, recycling initiatives have gained traction, including efforts to convert tires into flooring tiles and other applications. Leveraging tire recycling not only addresses waste management challenges but also provides an eco-friendly alternative for mitigating oil spill pollution [7].

Recycling used tires can be done in several ways; one is the mechanical process. At Green Rubber Recycling, we shred complete tires and separate the key components – rubber, steel, and fiber (C. [32]). Steel and fiber also go into further recycling or applications [42,59]. Interestingly, one of the products we produce is rubber crumb, which is further used to make a variety of flooring applications like tiles and mats [38]. They can be used in playgrounds, nurseries, car parks, walkways, medical applications, the uses are endless [16]. Despite its significant benefits, recycling tires for oil spill remediation faces challenges such as the need for further research to improve the efficiency of tire-derived materials and address concerns about potential chemical leaching [19].

The primary goal of this research is to evaluate the potential of environmentally friendly shredded tires as an oil sorbent, for its practical utility in removing oil from oil-contaminated water. The study's specific goals include (1) finding the optimum percentage of oil removed under diverse conditions (shaking time, shredded tire size, adsorbent dosages, oil concentration, temperature, pH, and reusability, and (2) interpreting the kinetics and adsorption isotherms to validate the experimental outcomes.

2. Material and methods

In this research, several types of shredded tires (rubber tire powder, fibers, 0.5–2 mm granules, 2.5–3.5 mm granules, and TDF (Tire-derived fuel) were used in this study. The shredded tire was brought from EPSCO Global Company in Kuwait. The 2.5–3.5 mm granules were grinded with a mortar and pestle, then passed through a mesh to obtain 0.5–2 mm granules. The crude oil (deep brown, API 32, specific gravity 0.865, 30 centipoises at room temperature) used in the study was supplied by an oil company in Kuwait. Recycled shredded tires were thoroughly washed with tap water to eliminate impurities, followed by several washes with distilled water, and then dried in an oven at 100 °C for a minimum of 24 hours until a constant weight was achieved. Analytical grade sodium hydroxide and hydrochloric acid, used for adjusting the pH, were bought from Sigma-Aldrich, USA. A hot magnetic plate was used to assess the effect of temperature on the rate of adsorptive oil removal. For the oil spill cleanup experiments, real seawater samples from the beach in Kuwait were used. Mini Rotary Shakers (REMI RS-12 Plus) with a capacity of 5 × 500 mL were purchased from IndiaMart.

2.1. Recycling tires process

The process of converting tires into tire powder, fiber, granules, and steel consists of multiple steps, each aimed at separating and reducing the tire's components into usable materials. The recycling process in the recycling waste tire factory in Kuwait involves the initial inspection and removal of contaminants for any non-rubber contaminants such as rims, dirt, and debris, which are removed manually or with machines. Then, the whole tires are fed into a primary shredder, which reduces them into large pieces, typically around 2–6 mm in size. Then, the large pieces are further processed in a secondary shredder to reduce them into smaller granules, usually ranging from 0.5 to 2 mm. This step begins to separate the tire's different components like steel where it's removed by a magnet and recycled separately. The remaining rubber and fiber are sent to further processing through granulators and screens to produce finer granules. At this stage, fiber separators are used to separate textile fibers from the rubber granules. Then, the rubber granules are ground into finer particles or tire powder using mills. Fig. 1 illustrates the tire shredding process, which breaks down tires into rubber tire powder, fiber, granules, and steel. The resulting screened materials—tire powder, fiber, granules, and steel—are then used to investigate their effectiveness in oil adsorption.

2.2. Tire composition and structure

Tires are composed of a complex blend of materials and chemicals designed to provide durability, flexibility, and performance. Fig. 2A and B show the chemical structure and composition of a tire [18]. The exterior tread to the interior lining of a tire is made of various materials, each with specific properties. The tread, which directly contacts the road, is primarily composed of natural rubber and synthetic rubbers. Depending on the tire's application (car, truck, off-the-road, etc.), belts can include rubber, steel, and textiles. The inner liner, which maintains air pressure, is made of butyl rubber, known for its low air permeability and good rolling resistance. The carcass and beads are made of twisted metal or textile cords and metal alloy-coated steel wires, respectively [46]. Shredded tire composition is highly effective for oil adsorption because of its large surface area, porosity, hydrophobicity, and durability, as indicated by earlier studies [54]. The presence of carbon black and other additives in tire rubber enhances its affinity for hydrocarbon-based substances like oil. These combined properties make shredded tires a highly efficient and sustainable choice for oil adsorption [23].

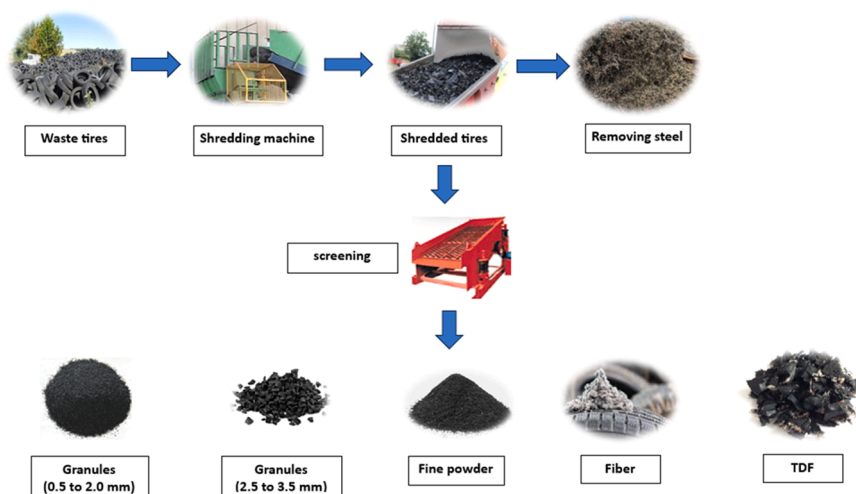


Fig. 1. Tires shredding process.

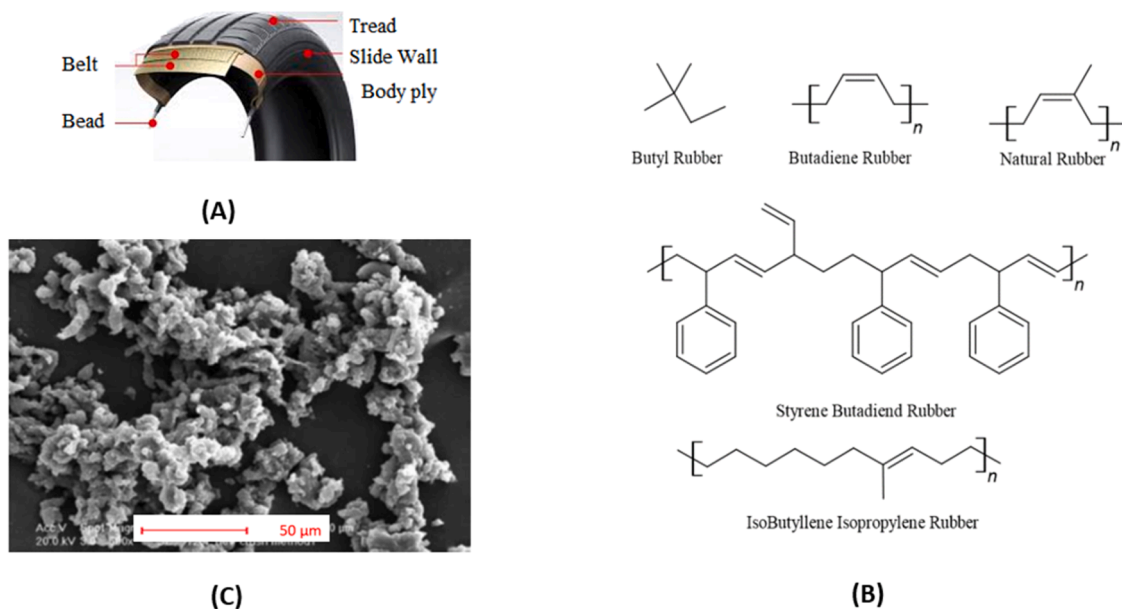


Fig. 2. (A) Tire composition; (B) chemical structure; (C) SEM photo of the screened tire powder.

2.3. Characterization of screen tire products

The waste tire rubber was processed using the grinding method, resulting in particles sized between 30 and 50 mm. In Fig. 2C, the scale bar in the SEM image of the powder shows a length of 50 mm [29].

2.4. Compositional analysis of shredded tires using XRF

The shredded tire material was subjected to X-ray fluorescence (XRF) analysis to determine its elemental composition. The analysis revealed that carbon, primarily from carbon black, constituted approximately 45 % of the material by weight, underscoring its role as a reinforcing agent and its potential for oil adsorption due to its hydrophobicity and large surface area. Sulfur, used in the vulcanization process, was identified at 2.3 %, indicating its contribution to the durability and elasticity of the rubber matrix. Zinc, detected at 1.8 %, reflects its use as an activator during vulcanization, while trace amounts of iron (0.7 %) were attributed to residual steel contamination. Additional elements such as silicon, magnesium, and calcium were found in small quantities, likely to originate from fillers and stabilizers added during tire manufacturing.

The compositional data supports the assertion that shredded tires possess properties such as porosity, hydrophobicity, and durability, making them a promising material for oil spill remediation.

2.5. BET surface area and porosity analysis

The Brunauer–Emmett–Teller (BET) method was employed to determine the tire materials' specific surface area, pore volume, and pore size distribution. The analysis was conducted using Micromeritics at 77 K liquid nitrogen temperature. Before the measurements, all samples were degassed under a vacuum at 120°C temperature for 12 hours to remove adsorbed moisture and contaminants. Nitrogen gas was used as an adsorbate, and adsorption-desorption isotherms were recorded. The specific surface area was calculated based on the BET theory, while the total pore volume was determined from the amount of nitrogen adsorbed at a relative pressure (P/P_0) of 0.99. The pore size distribution and average pore diameter were analyzed using the Barrett–Joyner–Halenda (BJH) method applied to the desorption branch of the isotherm. This procedure ensured accurate characterization of the material's surface area and porosity, providing key data to evaluate their

potential for adsorption applications.

2.6. Oil removal method

A removal process was conducted through batch experiments as follows: Initially, 4 g of crude oil was poured into a 250 mL glass flask containing 100 mL of seawater and left for 3 minutes to allow the oil layer to cover the surface of the seawater. Then, 2 g of shredded tire were added to the oil layer. The shredded tire with the adsorbed oil was carefully removed using a tweezer after agitation using a shaker (150 rpm) for 30 minutes at 25 °C and left to dry at room temperature for 72 hours to allow the unadsorbed oil to drip off. Additionally, samples of the shredded tire were dried in an oven at a temperature of 70°C until a constant weight was achieved. The adsorption experiment was conducted batchwise.

The effectiveness of oil adsorption was studied by varying different quantitative parameters such as shaking time (5, 10, 15, 20, 30, and 45 minutes) at 150 rpm, adsorbent dose (0.5, 1, 2, 3, 4 g, and 5 g), temperature (25, 45, 50, 65, 70, and 75°C), pH levels (2, 3, 5, 7, 9, and 10), oil concentration (10, 20, 30, 40, 50, and 60 g/L), and different types of shredded tires (rubber tire powder, fiber, 0.5–2.0 mm granules, 2.5–3.5 mm granules and TDF).

2.7. Calculation of oil removal and adsorption capacity

The percentage removal of oil (OR%) and adsorption capacity (g/g) by shredded tires were calculated using Eqs. 1 and 2 respectively, where C_i denotes the initial oil concentration in mg/L and C_e is the equilibrium oil concentration, V is the solution volume, (L) and the mass of the adsorbent utilized is M (g). Each experiment was conducted in triplicate, and the resultant average values were calculated and used in the analysis.

$$OR\% = (C_i - C_e) / (C_i) \times 100 \quad (1)$$

$$Q_e = (C_i - C_e) \times V / M \quad (2)$$

In the context of our study, C_i (initial oil concentration) and C_e (equilibrium oil concentration) specifically refer to the concentrations of oil present in the aqueous phase (seawater) during the adsorption experiments. These values were measured as follows:

2.7.1. Initial oil concentration (C_i)

C_i represents the amount of oil present in the aqueous phase (mg/L) at the beginning of the experiment, before the introduction of the adsorbent material (shredded waste tires). This was determined by thoroughly mixing a known quantity of oil in seawater, allowing the system to reach a state of dispersion, and measuring the oil content in the aqueous phase.

2.7.2. Equilibrium oil concentration (C_e)

C_e refers to the concentration of oil remaining in the aqueous phase (mg/L) after a fixed adsorption time, at which point no further significant reduction in oil concentration is observed. This is considered a pseudo-equilibrium state, as the adsorption process is not fully reversible or thermodynamically ideal due to the biphasic nature of the system and the possibility of irreversible adsorption. The aqueous phase was separated from the immiscible oil phase after the adsorption period, and C_e was measured using the same analytical technique used for C_i .

By defining C_i and C_e in this way, we focus exclusively on the oil concentration in the aqueous phase, which serves as the basis for calculating oil removal (OR%) and adsorption capacity (q_e) according to Eqs. (1) and (2). These definitions ensure consistency and comparability with other studies in the field of oil adsorption research.

2.8. Adsorption kinetics

The adsorption kinetics of crude oil on screened tire products were analyzed using the pseudo-first order and pseudo-second-order kinetic models. Pseudo-first order and pseudo-second-order kinetics were assessed for various screened tire products at oil concentrations of 40 g/L oil, 2 g adsorbent dosage, 100 mL seawater, 25°C, and pH 7.

According to the pseudo-first-order model, the adsorption process is viewed as physisorption, occurring without electron transfer. Eq. 3 represents the first-order model, wherein a linear plot of $\log(q_e - q_t)$ against t offers insight into the suitability of the pseudo-first-order kinetic model. The rate constant k_1 and the equilibrium amount of oil removed q_e can be derived from the slope ($-k_1/2.303$) and the intercept ($\log q_e$) of the plot [33].

$$\log(q_e - q_t) = \log q_e - k_1 t / 2.303 \quad (3)$$

Eq. 4 presents the generic representation of the pseudo-second-order kinetic model, where q_e denotes the oil adsorbed at equilibrium, q_t signifies the oil adsorbed at time t , K_2 stands for the second-order rate constant (measured in g/mg/min), and t represents time (in minutes) and denotes the rate constant of pseudo-second-order adsorption [36]. This kinetic model assumes that the adsorption process entails chemisorption, where a chemical bond forms between the adsorbate molecules and the adsorptive sites.

$$t/q_t = 1 / (K_2 * q_e^2) + t/q_e \quad (4)$$

2.9. Adsorption isotherm

In this study, the adsorption behavior of oil onto shredded waste tires was analyzed using Langmuir and Freundlich isotherm models. These models are widely employed in adsorption studies to describe the relationship between the adsorbate concentration in solutions and the amount adsorbed onto the adsorbent surface at equilibrium. Although these models are traditionally derived based on assumptions of thermodynamic equilibrium and reversible adsorption, they are also commonly used as empirical tools to describe adsorption in systems that may deviate from ideal equilibrium conditions.

The adsorption isotherm analysis for crude oil onto the screen tire products was performed at a constant room temperature of 25°C, 7 pH, 30 minutes shaking time, 10–60 g/L oil concentration at 0.5–5 g adsorbent dose utilizing two isotherm models: Langmuir, and Freundlich for various concentration of screen tire products. These models were developed based on varying assumptions and limitations [24].

In the context of the biphasic oil-water system studied here, the initial oil concentration (C_i) and the equilibrium oil concentration (C_e) refer specifically to the concentration of oil in the aqueous phase (mg/L). The pseudo-equilibrium state was assumed when no further significant changes in the oil concentration in the aqueous phase were observed, which served as the practical equilibrium point for calculating the adsorption capacity (q_e) using Eq. (5). While the oil adsorption onto the shredded tire surface may involve a degree of irreversibility, the Langmuir and Freundlich isotherms were applied to estimate parameters such as adsorption capacity and surface affinity, providing valuable comparative insights into the performance of shredded tires as adsorbents.

The Langmuir Isotherm posits that adsorption happens on a uniform surface holding a limited number of identical adsorption sites. Once a site is occupied, no more adsorptions can occur on that specific site. Furthermore, it suggests a monolayer-layer adsorption process, without any lateral interaction between the adsorbed molecules [50].

Eq. 5 presents the Langmuir model in its linear form, where q_e represents the adsorption capacity, C_e stands for the equilibrium concentration of the adsorbate, and q_m (mg/g) and K_L (L/mg) are Langmuir constants associated with the maximum adsorption capacity. According to this equation, if the adsorption follows the Langmuir equation,

plotting C_e/q_e against C_e should yield a straight line with a slope of $1/q_m$ and an intercept of $1/q_m * K_L$. The key characteristics of the Langmuir isotherm can be summarized using a dimensionless constant known as the separation factor (R_L , also referred to as the equilibrium parameter). It is defined by the following Eq. (6), where C_i (mg/L) is the initial oil concentration, and K_L (L/mg) is the Langmuir constant associated with the energy of adsorption. When R_L equals 1, it indicates a linear adsorption isotherm, which happens when K_L equals 0. If R_L equals 0, it suggests an irreversible adsorption isotherm, as K_L tends to infinity, indicating strong adsorption. R_L values greater than 1 and between 0 and 1 signify unfavorable and favorable adsorption processes, respectively.

The Freundlich Isotherm is well-suited for heterogeneous adsorption surfaces characterized by varying potential adsorption abilities at their active sites. In such scenarios, the stronger binding sites are typically occupied before the weaker ones. As more adsorption sites are filled, the potential adsorption (binding strength) of the active sites decreases. These exponential reductions in the binding energy of adsorption sites provide support for the concept of multilayer adsorption.

Freundlich model, represented by Eq. 7, features K_F as the Freundlich constant, indicating the adsorbent capacity (mg/g adsorbent), and $1/n$ as the surface heterogeneity parameter associated with the adsorption intensity [33].

$$\frac{C_e}{q_e} = \frac{1}{q_m * K_L} + \frac{C_e}{q_m} \quad (5)$$

$$R_L = \frac{1}{1 + K_L * C_i} \quad (6)$$

$$\ln q_e = \ln K_F + \frac{1}{n} \ln C_e \quad (7)$$

2.10. Adsorption experiments

In this study, batch adsorption experiments were conducted to determine the most effective operating parameters and to investigate the efficiency of oil adsorption on the adsorbent surface.

Fig. 3 presents a schematic and laboratory diagram of the oil adsorption experiment procedure using tire textile fiber. The study examined oil removal efficiency with several types of screened shredded tires under various conditions to find the optimal rate of oil removal.

Initially, the most easily accessible sites are occupied, and with additional time, oil molecules can move to and occupy less accessible sites, thereby enhancing the total amount of oil removed [36,37,56]. After 30 minutes, the plateau remained constant with no notable change in oil adsorption. Similar trends were seen for all the diverse types of shredded tires regarding shaking time and particle size. This shows that equilibrium can be achieved with 40 g/L of initial crude oil concentration and 2 g of shredded tire waste. It is also indicated from Fig. 4A that as the particle size increases, the oil removal efficiency decreases. The reason for this is that the smaller particles have a higher surface area-to-volume ratio compared to larger particles as shown in previous study [12].

This increased surface area provides more contact points for the oil to adhere to, enhancing the adsorption capacity [33,35,55].

Fig. 4B assesses the impact of increasing oil concentration (10, 20, 30,

3. Results and discussion

3.1. Effect of quantitative parameters on OR%

To assess the oil adsorption capacity of several types of shredded tires (tire powder, fiber, 0.5–2 mm, 2.5–3.5 mm granules, and TDF) for removing crude oil from seawater, various quantitative parameters were evaluated to identify the optimal conditions for oil adsorption and the percentage of oil adsorption OR% was evaluated.

Fig. 4 illustrates the average outcomes achieved for oil adsorption from oily seawater using various shredded tires while varying shaking time, oil weight, and temperature.

To figure out the time required to achieve optimal adsorption efficiency, the OR% was assessed at intervals of 5, 10, 15, 20, 30, and 45 minutes using 2 g of various shredded tires and 40 g/L of initial crude oil concentration, at 25°C and pH 7. Fig. 4A demonstrates that oil efficiency increased as shaking time increased until it reached maximum adsorption: 98.1 %, 97.0 %, 88.1 %, 80.2 %, and 71.1 % for tire powder, fiber, granules (0.5–2 mm), granules (2.5–3.5 mm), and TDF, respectively. The findings suggest that the maximum oil adsorption percentage was achieved at 30 minutes of shaking time for all types of shredded tire, reaching equilibrium, similar trend was found earlier utilizing fibrous sorbent under the same time [6]. Increased contact time enables oil molecules to reach and fill more adsorption sites on the adsorbent surface as mentioned in earlier studies [41,49]. This time, it was chosen to conduct all subsequent studies.

Initially, the most easily accessible sites are occupied, and with additional time, oil molecules can move to and occupy less accessible sites, thereby enhancing the total amount of oil removed [36,37,56]. After 30 minutes, the plateau remained constant with no notable change in oil adsorption. Similar trends were seen for all the diverse types of shredded tires regarding shaking time and particle size. This shows that equilibrium can be achieved with 40 g/L of initial crude oil concentration and 2 g of shredded tire waste. It is also indicated from Fig. 4A that as the particle size increases, the oil removal efficiency decreases. The reason for this is that the smaller particles have a higher surface area-to-volume ratio compared to larger particles as shown in previous study [12].

This increased surface area provides more contact points for the oil to adhere to, enhancing the adsorption capacity [33,35,55].

Fig. 4B assesses the impact of increasing oil concentration (10, 20, 30,

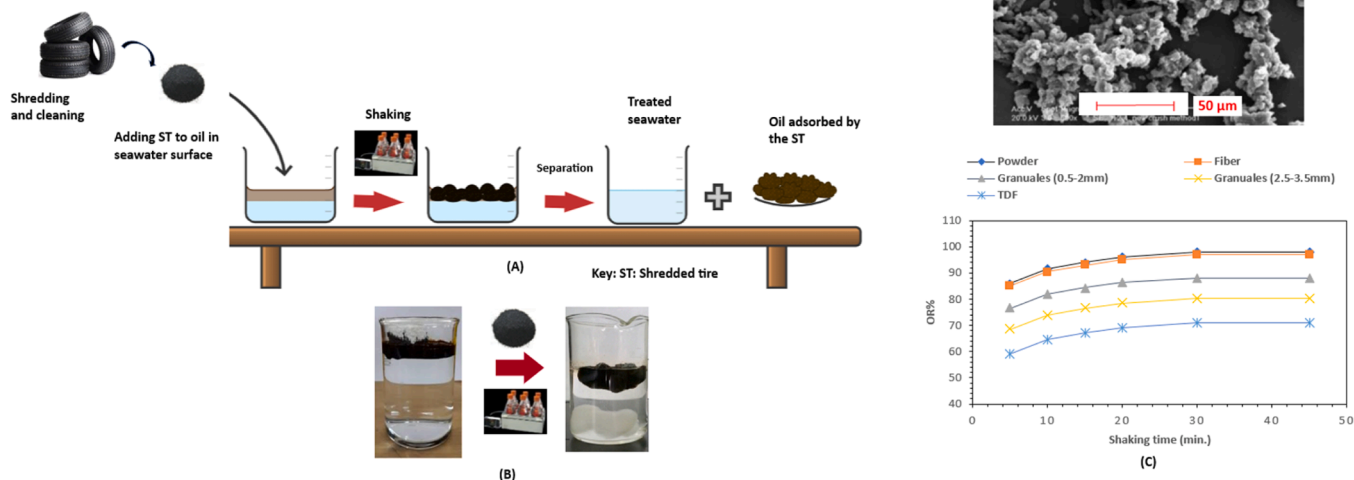


Fig. 3. Batch oil adsorption process using screened waste tire: (A) General schematic diagram of the oil adsorption process. (B) Laboratory setup for oil adsorption using textile fibers. (C) SEM images and an example of the effect of shaking time on oil adsorption efficiency.

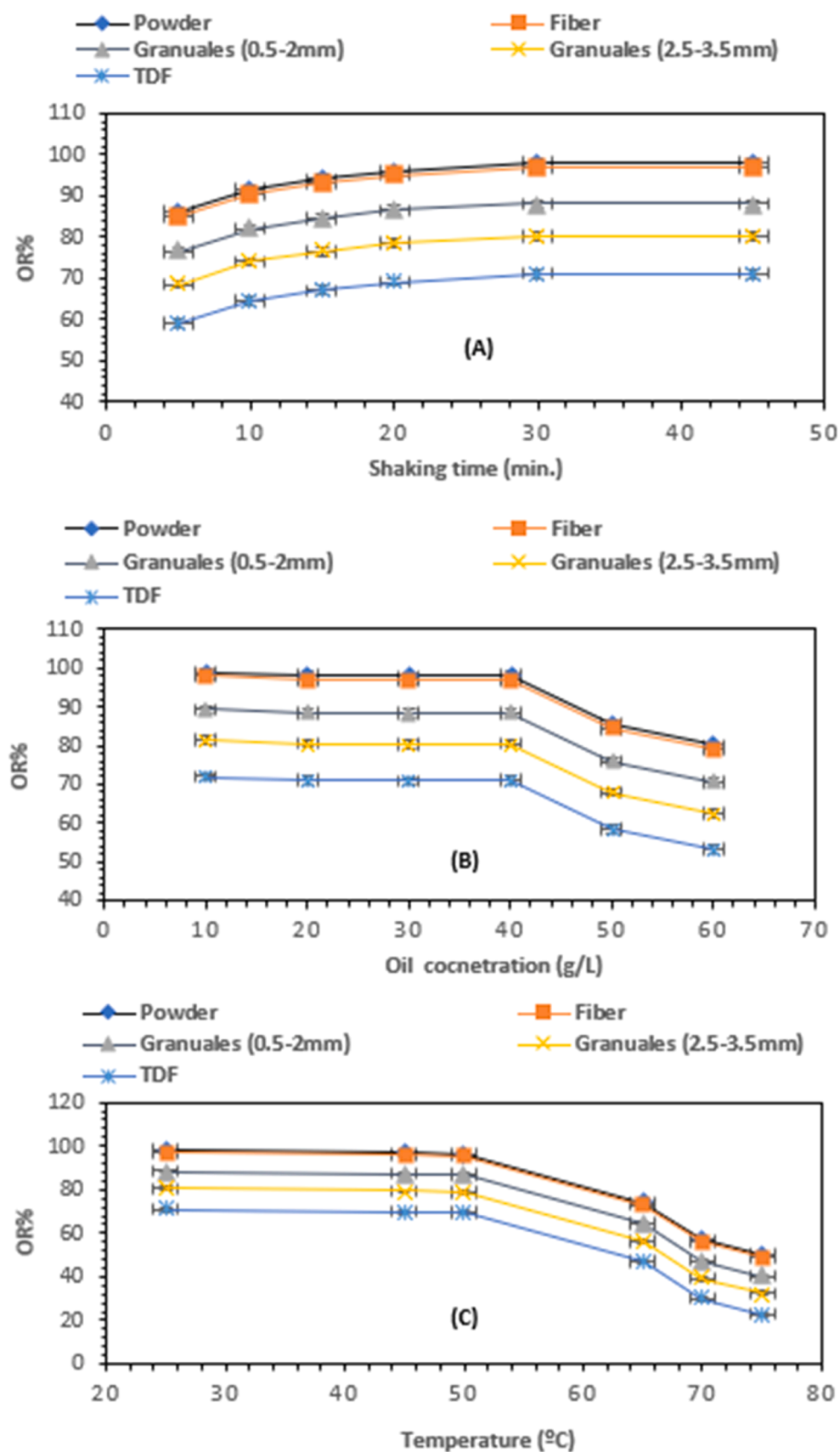


Fig. 4. Impact of (A) Shaking Time (B) Oil Weight (C) Temperature on Oil Removal Percentage for Different Types of Shredded Tire.

40, 50, and 60 g/L) with a shaking time of 30 minutes, at 25°C and pH 7, using 2 g of several types of shredded tire. It is clear from Fig. 4B that as the OR% decreases with the increase the oil concentration increases from 10 to 60 g/L for all the several types of shredded tire. This is due to the limited availability of active sites on the surfaces of shredded tires. At low initial crude oil concentrations, the ratio of active surface sites to crude oil is high, allowing more oil molecules to interact with and occupy the adsorbent's active sites, resulting in a high percentage of oil removal: 99.0 %, 97.9 %, 89.4 %, 81.4 %, and 72.0 % for tire powder, fiber, granules (0.5–2 mm), granules (2.5–3.5 mm), and TDF shredded tires, respectively. Conversely, when the initial crude oil concentration increases, the number of active adsorption sites becomes insufficient to accommodate all the oil molecules, leading to lower percentages of oil removal: 80.2 %, 79.1 %, 70.6 %, 62.6 %, and 53.2 % for the same materials.

The effect of temperature on oil removal efficiency was evaluated, as shown in Fig. 4C. Results indicated that increasing temperatures led to a decline in oil removal percentage (OR%) [56]. At higher initial oil concentrations, the sorbent surface reaches saturation quickly, leaving a significant amount of oil unattached [64].

Using 2 g of different shredded tire types, OR% was assessed across temperatures ranging from 25 to 75°C with 40 g/L of crude oil, a shaking time of 30 minutes, and pH 7. Fig. 4C shows that OR% decreased as temperature increased, with tire powder, fiber, granules (0.5–2 mm), granules (2.5–3.5 mm), and TDF exhibiting reductions from 98.0 % to 50.0 %, 97.0–55.9 %, 88.5–40.4 %, 80.5–32.4 %, and 71.1–23.0 %, respectively.

The maximum OR% for all shredded tire products was observed at 25°C, which was selected for subsequent experiments. Elevated temperatures reduce adsorption efficiency by lowering oil viscosity, thereby decreasing adhesion to the sorbent surface. This increased molecular mobility raises the likelihood of desorption, weakening the physical forces responsible for adsorption [51].

Consequently, the oil adsorbent's capacity to retain oil molecules diminishes, resulting in a decline in removal efficiency [52]. Moreover, higher temperatures can alter the physical structure of the shredded tire, making it more rigid and less effective. This alteration may lead to fewer oil molecules being adsorbed [21].

Fig. 5 presents the average results obtained for oil adsorption from oily seawater using diverse types of shredded tires, with adsorbent dosage, pH, and reusability variations. Fig. 5A demonstrates the impact of different adsorbent dosages (ranging from 1 g to 5 g) of shredded tire on oil adsorption efficiency while maintaining a shaking time of 30 minutes, an initial oil concentration of 40 g/L, a temperature of 25°C, and a pH of 7 for various shredded tire types.

The highest OR% was attained with a 2 g adsorbent dose, resulting in percentages of 98.1 %, 97.0 %, 88.5 %, 80.5 %, and 71.1 % for tire powder, fiber, granules (0.5–2 mm), granules (2.5–3.5 mm), and TDF, respectively. The results indicate that increasing the adsorbent dosage enhances OR% as shown in an earlier study using tire powder and polypropylene fiber [30]. It was observed that escalating the adsorbent dose led to a proportional increase in the percentage removal of oil from the adsorbent, as depicted in Fig. 5A. This increase in oil removal percentage with higher adsorbent doses is attributed to the augmentation in the number of active sorption sites available on the adsorbent's surface, a phenomenon consistent with previous studies [10]. Moreover, surpassing the 2 g threshold for adsorbent dosage did not result in further enhancements in oil adsorption. This observation suggests the attainment of a saturation point at 2 g of adsorbent, where maximal oil adsorption efficiency is reached. Therefore, 2 g was identified as the optimal dosage for all experiments, ensuring efficient oil recovery while minimizing material usage. Similar trends were observed across all shredded tire types; hence, this dosage was selected for all subsequent studies.

Determining the pH is essential to ensure the effectiveness, efficiency, and environmental compatibility of oil adsorption processes

using adsorbent materials [22]. Fig. 5B illustrates how the oil adsorption efficiency of shredded tire varies with different pH levels (ranging from 2 to 10). The experiment maintains a shaking time of 30 minutes, an adsorbent dose of 2 g, 40 g/L of initial crude oil concentration, and a temperature of 25°C across several types of shredded tires.

The oil removal percentage (OR%) shows an increase from pH 2–7 for the adsorbents (with results ranging from 82.9 % to 98.1 %, 81.8–97.0 %, 73.3–88.5 %, and 55.9–71.1 % for tire powder, fiber, granules (0.5–2 mm), and granules (2.5–3.5 mm) and TDF, respectively), then decreases to 97.2 %, 96.1 %, 87.6 %, 79.6 %, and 70.2 %, respectively, for tire powder, fiber, granules (0.5–2 mm), granules (2.5–3.5 mm), and TDF at pH 7–10. At pH levels below 7, the tire fiber's surface tends to become positively charged due to the protonation of its surface functional groups [48]. This positive charge enables it to attract oil molecules, which are typically negatively charged, thereby improving adsorption, as shown earlier [60]. However, as the pH rises from 7–10, the tire fiber's surface charge tends to diminish, possibly becoming neutral or even negative, resulting in decreased attraction to oil molecules [22]. The maximum OR% was attained at pH 7 for all the screened shredded materials and was therefore selected for all subsequent studies.

Shredded tire products contain functional groups such as carbonyl ($\text{C}=\text{O}$), hydroxyl (-OH), and other groups, which enhance oil adsorption through hydrophobic interactions, hydrogen bonding, and electrostatic attractions [4]; (H.-Y. [26,31]). Previous studies confirm that adsorption performance is primarily influenced by these groups [26]. Our findings align with this, as the oil removal percentage (OR%) increased from pH 2–7 before declining at higher pH levels. This trend reflects the protonation and deprotonation of functional groups, where lower pH enhances electrostatic interactions with oil molecules, while deprotonation above pH 7 weakens adsorption. These results are consistent with established literature [48]; [60]; [22].

To evaluate the reusability of the oil adsorption capacity of the screen-shredded tire products (tire powder, fiber, granules (0.5–2 mm), granules (2.5–3.5 mm), and TDF), the OR% was measured under the same conditions for cycles 2–10 and 20, using the oil-saturated adsorbent after each cycle. The mass of the oil-saturated adsorbent was calculated, and the regenerated adsorbent was pressed to squeeze out the excess oil before being reused for the next oil spill cleanup cycle.

As shown in Fig. 5C, the OR% of the oil-saturated adsorbent decreased from 98.1 % to 70.7 %, 97.0–69.6 %, 88.5–61.1 %, 80.5–53.1 %, and 71.1–43.7 % for tire powder, fiber, granules (0.5–2 mm), granules (2.5–3.5 mm), and TDF, respectively, after cycles 2–10 and 20.

Thus, it allows the adsorbent to be reused without compromising its structural integrity [54]. Tire powder, which exhibits greater oil adsorption compared to other screened tire products, is more elastic and can be reused multiple times with minimal impact on its oil adsorption capacity, as described in earlier research [44,61]. Results showed that the sorption capacity was not affected after 20 times of reuse. This is not surprising because the tire powder is made of rubber material with an elastic characteristic as illustrated in earlier study (C. [32]). Therefore, it can endure repeated mechanical pressing without degrading, allowing the recovery of the adsorbed oil (C. [32]), [27]. The significance of reusing adsorbents in oil spill cleanup cannot be overstated. It reduces costs by minimizing replenishment needs, enhancing cost-effectiveness, and minimizes waste production, lessening the environmental impact [9]. This sustainable approach enables continuous response efforts without disruptions from material replacement, streamlining logistics and boosting cleanup efficiency. In essence, adsorbent reusability improves the practicality, sustainability, and effectiveness of oil spill remediation. As a result, this action will decrease the worldwide and environmental consequences of waste pollution linked to untreated car tires [9,63].

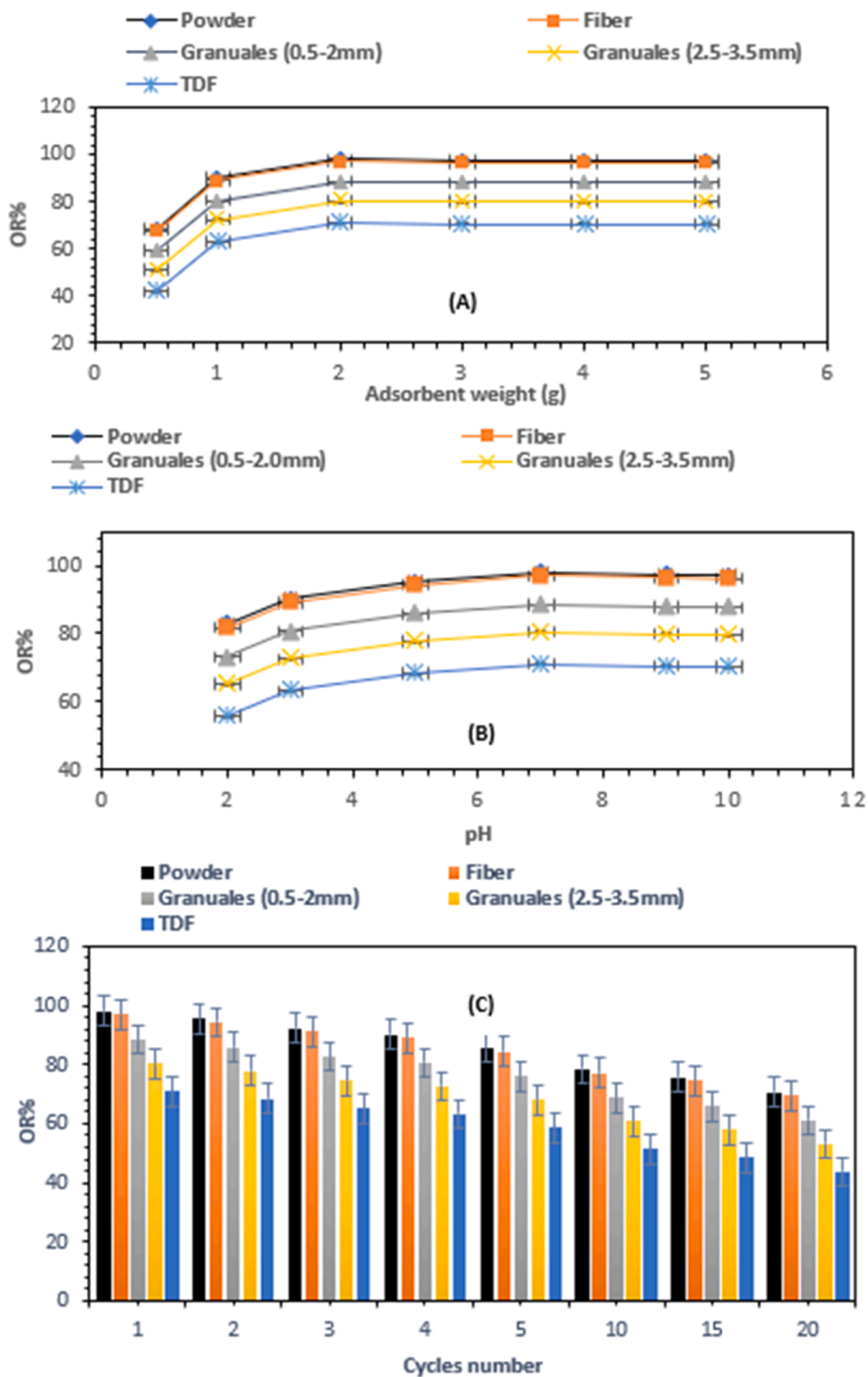


Fig. 5. Impact of (A) Adsorbent weight (B) pH (C) Reusability on Oil Removal Percentage for Different Types of Shredded Tire.

3.2. Adsorption kinetics

The kinetics of adsorption is a crucial parameter for assessing the remediation process. To understand the mechanism of crude oil spill remediation by screened tire products, the pseudo-first order and pseudo-second-order kinetic models were utilized. Both kinetic models were investigated to study the efficiency of oil adsorption using various screened tire products, and the results are demonstrated in Figs. 6A, 6B and Table 1. The study was conducted under the following conditions: a 2 g adsorbent dosage, 40 g/L oil concentration, 25 °C temperature, and a pH of 7.

The adsorption parameters for both first and second-order kinetic models were derived from the data presented in Figs. 6A, 6B, and the results are organized in Table 1. The results of the first-order kinetics (Fig. 6A) revealed that the oil adsorption capacity of tire powder (1.962 g/g) was higher compared to fiber (1.940 g/g), 0.5–2 mm granules (1.760 g/g), 2.5–3.5 mm granules (1.604 g/g), and TDF (1.422 g/g) at a fixed adsorbent dose of 2 g as shown in Table 1. This confirms the experimental results, showing that more oil can be removed from an oil spill using a 2 g dose of tire powder adsorbent. This could be due to the higher specific surface area of the tire powder adsorbent, which provides greater physical access for oil molecules. Furthermore, the increased surface area may result in a greater number of available binding sites on the adsorbent surface, facilitating enhanced oil adsorption [63]. The adsorption capacity for all screened tire waste was higher than that of zeolite reported in the literature. This result is due to the larger surface area of screened tire waste compared to the smaller surface area of zeolite [28].

Table 1 shows that the correlation coefficient R^2 values for the first-order kinetic model were 0.895, 0.880, 0.864, 0.862, and 0.857 for tire powder, fiber, 0.5–2 mm granules, 2.5–3.5 mm granules, and TDF, respectively. Since the R^2 for the first-order reaction is in this range, This implies that the process of oil binding to the screen tire products does

not follow a first-order reaction [3].

However, the straight linear line pattern observed in plot t/q_t vs. t graph (Fig. 6B) coupled with, R^2 values (Table 1) approaching 1 (≥ 0.999) across all screened tire adsorbents, provides compelling evidence that the oil adsorption by the screened rubber particles adheres to the second-order kinetic model. This indicates that the process of oil adsorption likely involves chemisorption and is probably influenced by the availability of active sites on the adsorbent surface and the concentration of the oil in the solution [3]. Moreover, the calculated q_e values in Table 1, derived from the second-order kinetic model, closely align with the experimental data. In contrast, the first-order kinetic model yields values that are notably lower and do not align well with the actual experimental values.

The rate constants for both models, i.e., k_1 and k_2 (Table 1), prove that tire powder has a higher and enhanced adsorption rate compared to all the rest of the screen tire products. The rate constant (k_2) value for tire powder using the second-order reaction was 0.611, compared to 0.599 for fiber, 0.549 for 0.5–2 mm granules, 0.521 for 2.5–3.5 mm granules, and 0.505 for TDF. The rate constants for both models, i.e., k_1 and k_2 , prove that tire powder has a higher and enhanced adsorption rate compared to the rest of the screen tire products.

3.3. Adsorption isotherm

Adsorption isotherms are essential for understanding the interaction between adsorbates and adsorbents [8,25]. The Langmuir and Freundlich models were applied to tire powder, identified as the most effective oil adsorbent, to estimate adsorption capacity and affinity.

As shown in Fig. 6C, Langmuir constants q_m and K_L were determined, with R^2 values ranging from 0.943 to 0.998 and q_m values between 1.10 and 15.44 g/g (Table 1). The RL values (0.635–0.758) confirm a favorable adsorption process. However, increasing initial oil concentration resulted in lower adsorption efficiency (Fig. 6A).

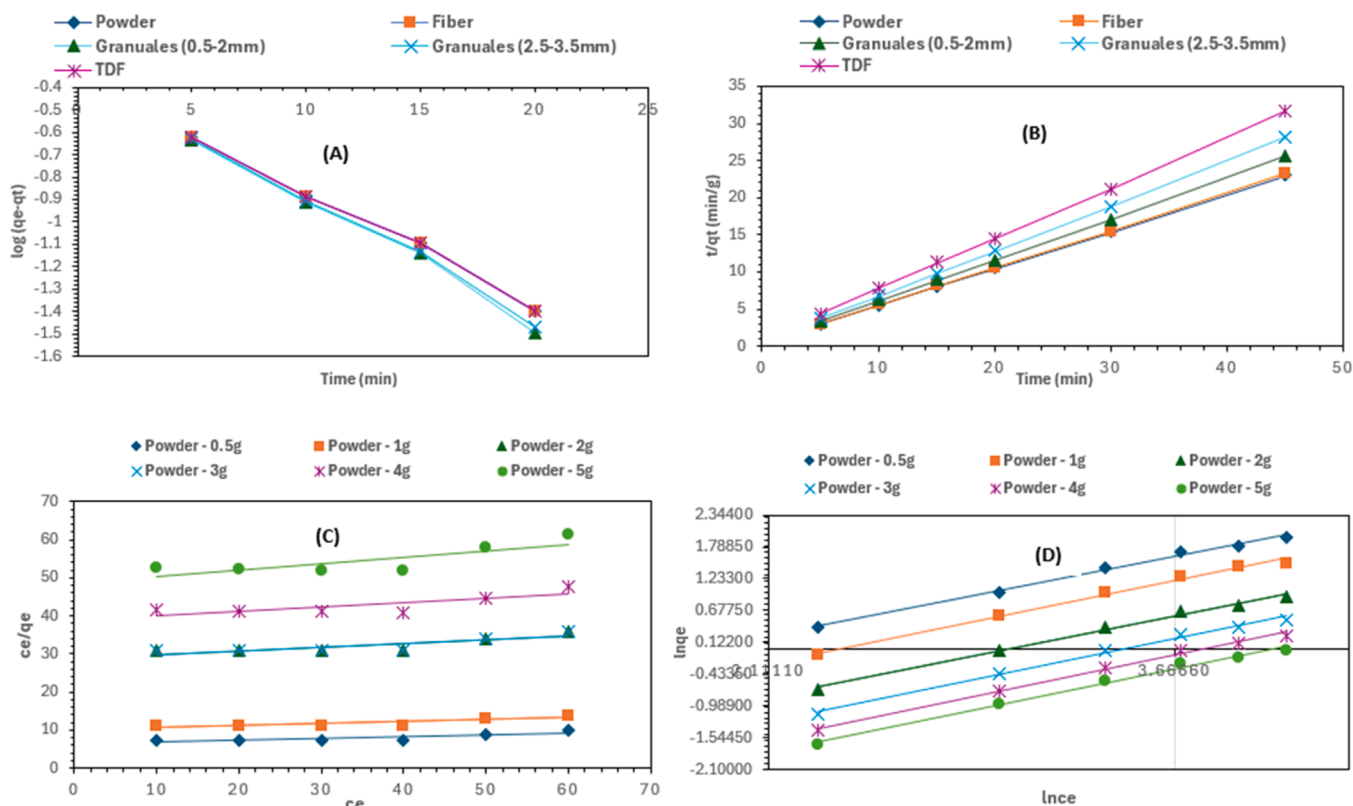


Fig. 6. Kinetic models using various screened tire products: (A) Pseudo-first order, (B) Pseudo-second order, at oil concentration 40 g/L, 25 °C, and pH 7. Adsorption isotherm for tire powder (C) Langmuir model (D) Freundlich model.

Table 1
Oil adsorption capacity and adsorption rate constants of screened tire products using pseudo first order, pseudo second-order models.

Adsorbent type		Parameter	Tire powder	Fiber	Granules (0.5–2 mm)	Granules (2.5–3.5 mm)	TDF
Adsorbent dosage (g)	Kinetic Model						
2 g	Pseudo First Order	Oil adsorption capacity (q) in g/g (experimental)	1.962	1.940	1.762	1.604	1.422
		k1 (min ⁻¹)	0.227	0.223	0.215	0.165	0.092
		qe (g/g) (calculated)	1.163	0.567	1.050	1.081	1.172
		R ²	0.895	0.880	0.864	0.862	0.857
	Pseudo Second order	k2 (g/g/min)	0.611	0.599	0.549	0.521	0.505
		qe (g/g) (calculated)	1.983	1.803	1.803	1.646	1.467
		R ²	0.999	0.999	0.999	0.999	0.999
Adsorbent dose (g)	Powder form Langmuir q _m (g/g)	K _L (L/g)	R ²	Freundlich			
				Average R _L	1/n	K _f	R ²
				0.758	0.891	0.1919	0.994
				0.702	0.925	0.1112	0.992
				0.640	0.910	0.0579	0.992
				0.635	0.933	0.0391	0.994
				0.640	0.939	0.0288	0.995
				0.640	0.931	0.0210	0.996
				0.640			

The Freundlich model, derived from Fig. 6D, suggests multilayer adsorption with R² values between 0.992 and 0.996, indicating a better fit than the Langmuir model. The 1/n values (0.891–0.939) suggest favorable physisorption and strong interactions between emulsified oil droplets and tire powder particles. While both models describe the adsorption data well, the Freundlich model provides the best fit (higher R² values).

Given the biphasic nature of the oil-water system and the strong retention of oil by the shredded tire, applying equilibrium models presents limitations. The irreversibility of adsorption, particularly under the tested conditions, challenges the assumptions of Langmuir and Freundlich isotherms. Instead, these models are used here as empirical tools for parameter estimation and comparison with literature data. Future research should explore alternative modeling approaches that better capture the complexities of biphasic adsorption systems and irreversible adsorption behavior.

3.4. BET surface area for tire materials (based on particle size)

The BET surface area analysis, presented in Table 2, compares tire powder, fiber, and granules. The results indicate that the adsorption efficiency of tire materials is influenced by their porosity,

hydrophobicity, and durability, all of which are related to particle size and surface area. Tire powder, with a high surface area (50–300 m²/g) and porosity (0.1–1.5 cm³/g), is highly effective in oil adsorption due to its large surface, hydrophobic nature, and mesopores that enhance oil uptake. Its durability makes it ideal for long-term applications like oil spill cleanup. On the other hand, tire fibers and granules, with lower surface area and porosity, have less adsorption capacity but offer greater durability. Thus, tire powder is better for oil adsorption, while fibers and granules are more durable but less efficient for this purpose.

Fig. 7 illustrates the relationship between particle size, BET surface area, porosity, and oil adsorption. Tire powder (0.5–2 mm), with the highest surface area (250 m²/g) and porosity (1.2 cm³/g), shows the best adsorption efficiency (90 %). Tire fibers (120 m²/g) and granules (80 m²/g), with lower surface area and porosity, have reduced adsorption efficiency (60 % and 40 %, respectively). Smaller particles like tire powder offer more active sites for adsorption, while larger particles, despite being hydrophobic, lack sufficient surface features for efficient

Table 2
BET surface area and porosity.

Material Type	Particle Size Range	BET Surface Area (m ² /g)	Porosity (Pore Volume, cm ³ /g)
Tire Powder	< 0.1 mm to 100 μm	50–300 m ² /g (can be higher with treatment)	0.1–1.5 cm ³ /g
Tire Fiber	0.5 mm to 2 mm	10–50 m ² /g	0.05–0.5 cm ³ /g
Granules (2.5–3.5 mm)	2.5 mm to 3.5 mm	5–30 m ² /g	0.02–0.3 cm ³ /g

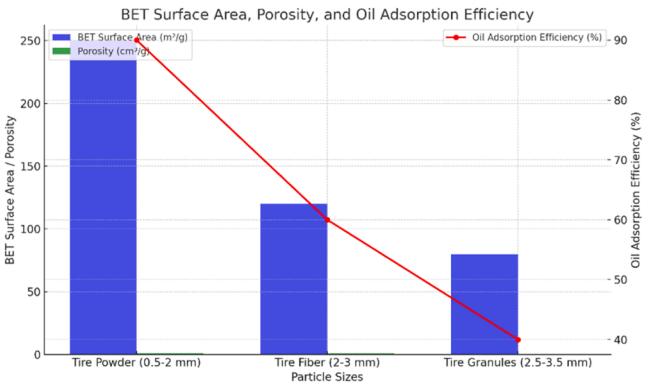


Fig. 7. BET surface area, porosity, and oil adsorption efficiency.

oil adsorption. In conclusion, tire powder is the most effective material for oil adsorption due to its high surface area, porosity, and adsorption efficiency. Tire fibers and granules, while more durable, are less effective for applications requiring high adsorption capacity.

3.5. Adsorption mechanisms

Fig. 8A illustrates the oil adsorption mechanism on tire powder and fiber, highlighting the differences in their adsorption processes. Oil adsorption on tire powder is primarily a physical process driven by its rough, porous structure and hydrophobic surface properties. Tire powder utilizes surface and pore diffusion due to its small particle size, high porosity, and large surface area, allowing oil molecules to diffuse along the surface and penetrate micropores. In contrast, tire fiber, with its elongated structure and lower porosity, primarily follows surface diffusion, where adsorption occurs predominantly on the external surface with minimal pore interactions.

Both tire powder and fiber exhibit surface diffusion as part of their oil adsorption mechanism, but their primary diffusion processes differ due to their structural characteristics. Tire powder, with its small particle size and high porosity, relies on surface and pore diffusion. Oil molecules initially diffuse along the surface to reach active sites and then penetrate the micropores for additional adsorption, making tire powder highly efficient. In contrast, tire fiber, characterized by its elongated structure and lower porosity, primarily follows surface diffusion, as most adsorption occurs on the external surface with limited internal pore interactions. Consequently, while both materials employ surface diffusion, tire powder's ability to utilize pore diffusion significantly enhances its overall adsorption efficiency compared to tire fiber.

The tire powder's hydrophobicity enhances oil retention, and adsorption is facilitated through weak van der Waals forces, forming a thin oil layer on the surface. This process follows a pseudo-second-order kinetic model, where the adsorption rate slows as the surface sites become occupied. With an adsorption efficiency of up to 98.1 %, tire powder demonstrates superior performance due to its ability to combine hydrophobic interactions, capillary action, and chemisorption, leading to stronger oil binding over time. These properties make tire powder highly effective and reusable for oil spill cleanup, outperforming tire fiber in adsorption efficiency and retention capacity.

The study demonstrates that oil adsorption on screened tire-derived adsorbents adheres to the pseudo-second-order kinetic model, with R^2 values exceeding 0.99990, indicating chemisorption as the dominant mechanism (Fig. 8B). Tire powder exhibited the highest adsorption capacity of 1.983 g/g and rate constant ($k_2 = 0.611$ g/g/min), attributed to its smaller particle size and larger surface area as shown in Table 1. In comparison, TDF had the lowest q_e (1.467 g/g, $k_2 = 0.505$ g/g/min), likely due to diffusion limitations. Granules and fiber showed intermediate performance, highlighting the role of particle size and surface area

in adsorption efficiency. The rapid adsorption phase followed by equilibrium across all materials confirms the effectiveness of the conditions (25°C, pH 7, and 2 g adsorbent dosage) in facilitating oil removal, with tire powder emerging as the most efficient adsorbent for such applications.

3.6. Comparison of adsorption capacity for oil removal

The adsorption capacity of this study and other previously studied data are presented in Table 3. Accordingly, the obtained removal capacity of this study using tire powder was found to be as significant as the other studied data listed in Table 2.

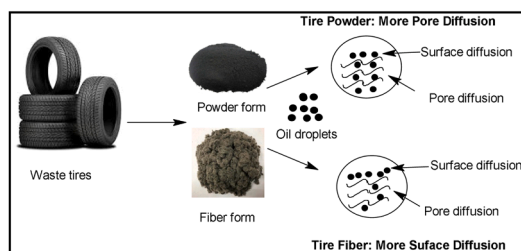
4. Conclusion

Waste tires are abundant and typically low-cost as they are often considered waste. utilize them as adsorbents reduces disposal costs and provides an economical source of raw material. Batch adsorption experiments effectively removed oil from oil spills, and the study's findings show that all tested materials possess oil-adsorbing capabilities. Optimal oil adsorption efficiency was achieved using a 2 g adsorbent dosage, at 25 °C, and with a 40 g/L oil concentration. The highest oil removal percentage (OR%) of 98.1 % was observed with rubber tire powder over other screened tire products due to its larger surface area, smaller pores with greater volume thereby enhancing its effectiveness in oil adsorption. Furthermore, increasing doses of adsorbent and decreasing granule sizes were associated with higher oil adsorption rates. The reusability tests showed that this tire powder adsorbent can achieve a 70.1 OR% after 20 cycles. The adsorption of oil adheres to pseudo-second-order kinetics, suggesting that the process is chemisorption-controlled, and that the adsorption rate depends on both the concentration of the oil and

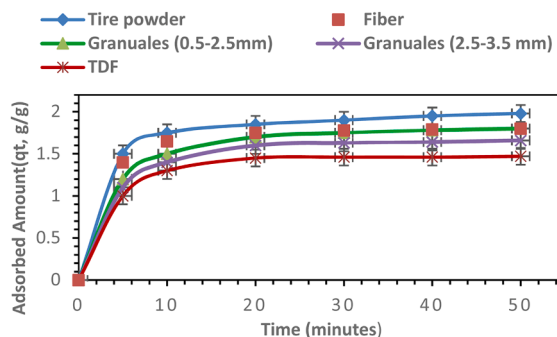
Table 3

Comparison of the adsorption capacity with other materials.

Adsorbent	Removal Capacity q_m	Reference
Tire powder	15.44 g/g (15,440 mg/g)	This study
Granular activated carbon:	1087.3 (mg/g)	Patel [45]
Modified Natural Fibers	11.0 g/g (11,000 mg/g)	Abdelwahab et al. [1]
Peanut husk	42.13 mg/g	Song et al. [53]
hydrolyzed fiber	16.78 g/g (16,780 mg/g)	Al Zubaidi et al. [6]
Rice husk	40 mg/g	Vadivelan and Kumar [57]
Sawdust	5.2 g/g (5200 mg/g)	Al Zubaidi et al. [6]
Chitosan Powder	0.55–0.6 g/g (550–600 mg/g)	Ahmad et al. [3]
Fibrous sorbent	15.45 g/g (15,450 mg/g)	Al Zubaidi et al. [6]
Rubber aerogel	25.0 g/g (25,000 mg/g)	Thai et al. [54]



(A)



(B)

Fig. 8. Oil adsorption mechanism. (A) on tire powder and fiber. (B) adsorption mechanism on Tire powder, fiber, granules, and TDF following Pseudo second order model.

the availability of adsorption sites on the adsorbent. Batch equilibrium adsorption was highly satisfactorily described by the Freundlich isotherm, with the largest adsorption capacity of 15.44 g/g at a low powder adsorbent dosage. Future studies can focus on the applications of finely ground rubber particles as residuals from the cleaning process. Efforts should be made to enhance the oil sorption ability of screened waste tire without compromising its reusability, reducing the need for frequent replacement and thereby lowering operational costs. By reusing tires, municipalities and industries can save on waste management costs associated with tire disposal, including landfill fees and potential environmental penalties. Further research should focus on optimizing the use of shredded waste tires adsorption capacity and exploring its application in large-scale, real-world scenarios.

Declaration and verification

Submission of an article implies that the work described has not been published previously.

Funding

The research study and the preparation of paper was done without any external source of funding.

CRediT authorship contribution statement

Salah Sara: Resources, Methodology, Formal analysis. **Malhas Rana:** Writing – review & editing, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Alawadhi Mariam:** Writing – original draft, Methodology, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors wish to express their gratitude to the Australian University for allowing them to use their laboratory facilities for their research endeavors.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.jece.2025.116133](https://doi.org/10.1016/j.jece.2025.116133).

Data availability

The authors confirm that the data supporting the findings of this study are available within the article, and the data will be available on request.

References

- [1] O. Abdelwahab, W. Thabet, S. Nasr, S. Nafea, Oil spill cleanup using chemically modified natural fibers: trial for practical application, Egypt. J. Aquat. Biol. Fish. 25 (2021) 457–464.
- [2] Y.K. Adofo, E. Nyankson, B. Agyei-Tuffour, Dispersants as an oil spill clean-up technique in the marine environment: a review, Heliyon 8 (2022) e10153, <https://doi.org/10.1016/j.heliyon.2022.e10153>.
- [3] A. Ahmad, S. Sumathi, B. Hameed, Adsorption of residue oil from palm oil mill effluent using powder and flake chitosan: equilibrium and kinetic studies, Water Res. 39 (2005) 2483–2494, <https://doi.org/10.1016/j.watres.2005.03.035>.
- [4] K.Z. Ahmed, M. Faizan, Comprehensive characterization of waste tire rubber powder, J. Inst. Eng. India Ser. E 105 (2024) 11–20, <https://doi.org/10.1007/s40034-023-00282-8>.
- [5] F.A. Aisien, F.K. Hymore, R.O. Ebebele, Comparative absorption of crude oil from fresh and marine water using recycled rubber, J. Environ. Eng. 132 (2006) 1078–1081, [https://doi.org/10.1061/\(ASCE\)0733-9372\(2006\)132:9\(1078\)](https://doi.org/10.1061/(ASCE)0733-9372(2006)132:9(1078)).
- [6] I.A.H. Al Zubaidi, A.K. Al Tamimi, H. Ahmed, Remediation of water from crude oil spill using a fibrous sorbent, Environ. Technol. Innov. 6 (2016) 105–114, <https://doi.org/10.1016/j.eti.2016.08.002>.
- [7] M. Al-Bared, A. Marto, N. Latifi, Utilization of recycled tiles and tyres in stabilization of soils and production of construction materials-a state-of-the-art review, KSCE J. Civ. Eng. 22 (2018) 1–15, <https://doi.org/10.1007/s12205-018-1532-2>.
- [8] M.A. Al-Ghouti, D.A. Da'ana, Guidelines for the use and interpretation of adsorption isotherm models: a review, J. Hazard. Mater. 393 (2020) 122383, <https://doi.org/10.1016/j.jhazmat.2020.122383>.
- [9] Aljammal, N., Yuzakova, T., 2016. Review on the Effectiveness of Adsorbent Materials in Oil Spills Clean Up.
- [10] J.A. Al-Najar, S.T. Al-Humairi, T. Lutfee, D. Balakrishnan, I. Veza, M.E. M. Soudagar, I.M.R. Fattah, Cost-effective natural adsorbents for remediation of oil-contaminated water, Water 15 (2023) 1186, <https://doi.org/10.3390/w15061186>.
- [11] Z. Asif, Z. Chen, C. An, J. Dong, Environmental impacts and challenges associated with oil spills on shorelines, JMSE 10 (2022) 762, <https://doi.org/10.3390/jmse10060762>.
- [12] D. Danwanichakul, P. Danwanichakul, P. Kaeomani, Kinetic modeling of oil absorption by waste tire granules. in: Proceedings of the Third International Conference on Advances In Civil, Structural and Environmental Engineering-ACSEE 2015. Presented at the Third International Conference on Advances In Civil, Structural and Environmental Engineering- ACSEE 2015, Institute of Research Engineers and Doctors, 2015, pp. 7–11, <https://doi.org/10.15224/978-1-63248-065-1-33>.
- [13] B. Doshi, M. Sillanpää, S. Kalliola, A review of bio-based materials for oil spill treatment, Water Res. 135 (2018) 262–277, <https://doi.org/10.1016/j.watres.2018.02.034>.
- [14] P. Ekins, D. Zenghelis, The costs and benefits of environmental sustainability, Sustain Sci. 16 (2021) 949–965, <https://doi.org/10.1007/s11625-021-00910-5>.
- [15] N. El Moussaoui, B. Idelhakkar, The impact of oil spills on the economy and the environment, EJEFR 7 (2023), <https://doi.org/10.46827/ejefr.v7i4.1570>.
- [16] M.M. El-Maadawy, A.A. Elzoghby, A.M. Masoud, Z.M. El-Deeb, A.M.A. El Naggari, M.H. Taha, Conversion of carbon black recovered from waste tires into activated carbon via chemical/microwave methods for efficient removal of heavy metal ions from wastewater, RSC Adv. 14 (2024) 6324–6338, <https://doi.org/10.1039/D4RA00172A>.
- [17] A. Fazli, D. Rodrigue, Waste rubber recycling: a review on the evolution and properties of thermoplastic elastomers, Materials 13 (2020) 782, <https://doi.org/10.3390/ma13030782>.
- [18] A. Fazli, D. Rodrigue, Recycling waste tires into ground tire rubber (gtr)/rubber compounds: a review, J. Compos. Sci. 4 (2020) 103, <https://doi.org/10.3390/jcs4030103>.
- [19] K. Formela, Sustainable development of waste tires recycling technologies – recent advances, challenges and future trends, Adv. Ind. Eng. Polym. Res. 4 (2021) 209–222, <https://doi.org/10.1016/j.aiepr.2021.06.004>.
- [20] S. Ghafoori, M. Omar, N. Koutahzadeh, S. Zendeheboudi, R.N. Malhas, M. Mohamed, S. Al-Zubaidi, K. Redha, F. Baraki, M. Mehrvar, New advancements, challenges, and future needs on treatment of oilfield produced water: A state-of-the-art review, Sep. Purif. Technol. 289 (2022) 120652, <https://doi.org/10.1016/j.seppur.2022.120652>.
- [21] L. Guelmine, H. Hadjab, A. Benazzouk, Effect of elevated temperatures on physical and mechanical properties of recycled rubber mortar, Constr. Build. Mater. 126 (2016) 77–85, <https://doi.org/10.1016/j.conbuildmat.2016.09.018>.
- [22] A.S. Gulistan, T.H. Ibrahim, M.I. Khamis, Y. ElSayed, Application of eggplant peels powder for the removal of oil from produced water, Desalin. Water Treat. 57 (2016) 15724–15732, <https://doi.org/10.1080/19443994.2015.1130661>.
- [23] V.K. Gupta, A. Nayak, S. Agarwal, I. Tyagi, Potential of activated carbon from waste rubber tire for the adsorption of phenolics: effect of pre-treatment conditions, J. Colloid Interface Sci. 417 (2014) 420–430, <https://doi.org/10.1016/j.jcis.2013.11.067>.
- [24] H. Hamed, N. Rezaei, S. Zendeheboudi, Investigation of emulsified oil adsorption onto functionalized magnetic nanoparticles—kinetic and isotherm models, Energies 16 (2023) 8073, <https://doi.org/10.3390/en16248073>.
- [25] A. Hani, N. Meftah, L. Zeghoud, A. Sdiri, A.H. Jawad, Statistical optimization and desirability function for producing nano silica from dune sand by sol–gel method towards Methylene Blue dye removal, J. Inorg. Organomet Polym. 33 (2023) 1882–1897, <https://doi.org/10.1007/s10904-023-02612-0>.
- [26] C. Hu, S. Hu, P. Fang, Z. Tang, X. Xiao, H. Wu, Waste-tire-derived activated carbon as efficient adsorbent of p-nitrophenol from wastewater, J. Chem. 2022 (2022) 1–12, <https://doi.org/10.1155/2022/7313899>.
- [27] D.M. Kasote, Y.S. Badhe, M.V. Hegde, Effect of mechanical press oil extraction processing on quality of linseed oil, Ind. Crops Prod. 42 (2013) 10–13, <https://doi.org/10.1016/j.indcrop.2012.05.015>.
- [28] E.H. Khader, T.J. Mohammed, S.W. Adnan, Reduction of oil and COD from produced water by activated carbon, zeolite, and mixed adsorbents in a fixed-bed column, DWT 227 (2021) 216–227, <https://doi.org/10.5004/dwt.2021.27295>.
- [29] J.K. Kim, S.H. Lee, M. Balasubramanian, A comparative study of effect of compatibilization agent on untreated and ultrasonically treated waste ground

- rubber tire and polyolefin blends, *Polímeros* 16 (2006) 263–268, <https://doi.org/10.1590/S0104-14282006000400004>.
- [30] C. Lin, Y.-J. Hong, A.H. Hu, Using a composite material containing waste tire powder and polypropylene fiber cut end to recover spilled oil, *Waste Manag.* 30 (2010) 263–267, <https://doi.org/10.1016/j.wasman.2009.03.001>.
- [31] C. Lin, C.-L. Huang, C.-C. Shern, Recycling waste tire powder for the recovery of oil spills, *Resour., Conserv. Recycl.* 52 (2008) 1162–1166, <https://doi.org/10.1016/j.resconrec.2008.06.003>.
- [32] H.-Y. Lin, W.-C. Chen, C.-S. Yuan, C.-H. Hung, Surface functional characteristics (C, O, S) of waste tire-derived carbon black before and after steam activation, *J. Air Waste Manag. Assoc.* 58 (2008) 78–84, <https://doi.org/10.3155/1047-3289.58.1.78>.
- [33] R. Malhas, T. Alamgir, A. Benhusain, N. Alotaibi, N. Alhaddad, Oil content removal from oil water emulsion by super magnetic nanoparticles, *J. Water Process Eng.* 55 (2023) 104246, <https://doi.org/10.1016/j.jwpe.2023.104246>.
- [34] R. Malhas, Y. Al-Ibrahim, A. Al-Meraj, H. Abdullah, A. Alshatti, Application of magnetic separation for oil spill remediation and recovery in Kuwait sea water, *DWT* 209 (2021) 114–120, <https://doi.org/10.5004/dwt.2021.26498>.
- [35] R. Malhas, Y. Al-Ibrahim, A. Al-Meraj, H. Abdullah, A. Alshatti, Application of magnetic separation for oil spill remediation and recovery in Kuwait sea water, *DWT* 209 (2021) 114–120, <https://doi.org/10.5004/dwt.2021.26498>.
- [36] R. Malhas, J.H. El Achkar, B. Misbah, S. Al Radhwan, Optimizing oil removal from oil-water emulsions using novel iron oxide magnetic nanoparticles, *Water Air Soil Pollut.* 234 (2023) 564, <https://doi.org/10.1007/s11270-023-06590-4>.
- [37] R.N. Malhas, K.W. Amadi, Oil removal from polluted seawater using carbon avocado peel as bio-absorbent, *EJENG* 8 (2023) 26–32, <https://doi.org/10.24018/ejeng.2023.8.2.3004>.
- [38] M.K. Mistry, S.J. Shukla, C.H. Solanki, Reuse of waste tyre products as a soil reinforcing material: a critical review, *Environ. Sci. Pollut. Res.* 28 (2021) 24940–24971, <https://doi.org/10.1007/s11356-021-13522-4>.
- [39] A.F. Mohammad, A.A.-H.I. Mourad, E. Galiwango, E.G. Lwisa, A.H. Al-Marzouqi, M.H. El-Naas, B. Van Der Bruggen, M.H. Al-Marzouqi, Effective and sustainable adsorbent materials for oil spill cleanup based on a multistage desalination process, *J. Environ. Manag.* 299 (2021) 113652, <https://doi.org/10.1016/j.jenvman.2021.113652>.
- [40] A.F. Mohammad, A.A.-H.I. Mourad, E. Galiwango, E.G. Lwisa, A.H. Al-Marzouqi, M.H. El-Naas, B. Van Der Bruggen, M.H. Al-Marzouqi, Effective and sustainable adsorbent materials for oil spill cleanup based on a multistage desalination process, *J. Environ. Manag.* 299 (2021) 113652, <https://doi.org/10.1016/j.jenvman.2021.113652>.
- [41] K. Okiel, M. El-Sayed, M.Y. El-Kady, Treatment of oil–water emulsions by adsorption onto activated carbon, bentonite and deposited carbon, *Egypt. J. Pet.* 20 (2011) 9–15, <https://doi.org/10.1016/j.ejpe.2011.06.002>.
- [42] A.A. Olajire, Recent advances on the treatment technology of oil and gas produced water for sustainable energy industry-mechanistic aspects and process chemistry perspectives, *Chem. Eng. J. Adv.* 4 (2020) 100049, <https://doi.org/10.1016/j.cej.2020.100049>.
- [43] D. Ouyang, X. Lei, H. Zheng, Recent advances in biomass-based materials for oil spill cleanup, *Nanomaterials* 13 (2023) 620, <https://doi.org/10.3390/nano13030620>.
- [44] J. Park, J.-Y. An, J.-E. Park, D. Bang, B.-S. Kim, M.-H. Oh, A study on the characteristic of waste ground rubber tire powders with pre-treatment process for recycling, *J. Korean Inst. Resour. Recycl.* 24 (2015) 55–61, <https://doi.org/10.7844/kiir.2015.24.2.55>.
- [45] H. Patel, Comparison of batch and fixed bed column adsorption: a critical review, *Int. J. Environ. Sci. Technol.* 19 (2022) 10409–10426, <https://doi.org/10.1007/s13762-021-03492-y>.
- [46] B. Rodgers, W. Waddell, The science of rubber compounding. Science and Technology of Rubber, Elsevier, 2005, pp. 401–454, <https://doi.org/10.1016/B978-012464786-2/50012-2>.
- [47] Rout, C., Sharma, A., 2013. Oil Spill in Marine Environment: Fate and Effects.
- [48] T.A. Saleh, V.K. Gupta, A.A. Al-Saadi, Adsorption of lead ions from aqueous solution using porous carbon derived from rubber tires: experimental and computational study, *J. Colloid Interface Sci.* 396 (2013) 264–269, <https://doi.org/10.1016/j.jcis.2013.01.037>.
- [49] P. Sharma, H. Kaur, Sugarcane bagasse for the removal of erythrosin B and methylene blue from aqueous waste, *Appl. Water Sci.* 1 (2011) 135–145, <https://doi.org/10.1007/s13201-011-0018-x>.
- [50] S. Shimizu, N. Matubayasi, Understanding sorption mechanisms directly from isotherms, *Langmuir* 39 (2023) 6113–6125, <https://doi.org/10.1021/acs.langmuir.3c00256>.
- [51] Y. Shin, K.S. Han, B.W. Arey, G.T. Bonheyo, Cotton fiber-based sorbents for treating crude oil spills, *ACS Omega* 5 (2020) 13894–13901, <https://doi.org/10.1021/acsomega.0c01290>.
- [52] Kutluay Siirt University, S. Baytar, O. Siirt University, Şahin, Ö. Siirt University, Adsorption kinetics, equilibrium and thermodynamics of gas-phase toluene onto char produced from almond shells, *Res. Eng. Struct. Mat.* (2019), <https://doi.org/10.17515/resm2019.73en1122>.
- [53] J. Song, W. Zou, Y. Bian, F. Su, R. Han, Adsorption characteristics of methylene blue by peanut husk in batch and column modes, *Desalination* 265 (2011) 119–125, <https://doi.org/10.1016/j.desal.2010.07.041>.
- [54] Q.B. Thai, D.K. Le, N.H.N. Do, P.K. Le, N. Phan-Thien, C.Y. Wee, H.M. Duong, Advanced aerogels from waste tire fibers for oil spill-cleaning applications, *J. Environ. Chem. Eng.* 8 (2020) 104016, <https://doi.org/10.1016/j.jece.2020.104016>.
- [55] O. Torsæter, Application of nanoparticles for oil recovery, *Nanomaterials* 11 (2021) 1063, <https://doi.org/10.3390/nano11051063>.
- [56] A. Ukpong, G. Habor, I. Obboh, Adsorption studies of oil spill clean-up using coconut coir activated carbon (CCAC), *Open Chem. Eng. J.* 8 (2020) 36–47, <https://doi.org/10.11648/j.ajche.20200802.11>.
- [57] V. Vadivelan, K.V. Kumar, Equilibrium, kinetics, mechanism, and process design for the sorption of methylene blue onto rice husk, *J. Colloid Interface Sci.* 286 (2005) 90–100, <https://doi.org/10.1016/j.jcis.2005.01.007>.
- [58] P.G. Wells, The iconic Torrey Canyon oil spill of 1967 - Marking its legacy, *Mar. Pollut. Bull.* 115 (2017) 1–2, <https://doi.org/10.1016/j.marpolbul.2016.12.013>.
- [59] Z. Xiao, A. Pramanik, A.K. Basak, C. Prakash, S. Shankar, Material recovery and recycling of waste tyres-A review, *Clean. Mater.* 5 (2022) 100115, <https://doi.org/10.1016/j.clema.2022.100115>.
- [60] J. Yu, S. Tian, A. Yao, H. Hu, J. Lan, L. Yang, X. Du, S. Lin, Compressible polydopamine modified pomelo peel powder/poly(ethyleneimine)/κ-carrageenan aerogel with pH-tunable charge for selective removal of anionic and cationic dyes, *Carbohydr. Polym.* 323 (2024) 121377, <https://doi.org/10.1016/j.carbpol.2023.121377>.
- [61] Z. Zamiraei, M. Golriz, M. Parsa, Applying recyclable waste tire for crude oil absorption, *J. Curr. Chem. Pharm. Sc.* 08 (2018), <https://doi.org/10.21767/2277-2871.1000110>.
- [62] M. Zamparas, D. Tzivras, V. Dracopoulos, T. Ioannides, Application of sorbents for oil spill cleanup focusing on natural-based modified materials: a review, *Molecules* 25 (2020) 4522, <https://doi.org/10.3390/molecules25194522>.
- [63] M. Zamparas, D. Tzivras, V. Dracopoulos, T. Ioannides, Application of sorbents for oil spill cleanup focusing on natural-based modified materials: a review, *Molecules* (2020), <https://doi.org/10.3390/molecules25194522>.
- [64] A.Y. Zekri, O. Chaalal, Effect of temperature on biodegradation of crude oil, *Energy Sources* 27 (2005) 233–244, <https://doi.org/10.1080/00908310490448299>.

Article

Critical Success Factors for the Widespread Adoption of Virtual Alternative Dispute Resolution (VADR) in the Construction Industry: A Structural Equation Modeling Analysis

Mohamed Salem ¹, Ruqaya S. Al-Sabah ², Mohamed T. Elnabwy ^{3,4}, Emad Elbeltagi ⁵ and Mohamed Tantawy ^{6,*}

¹ Department of Civil Engineering, College of Engineering, Australian University of Kuwait, Safat, West Mishref 13015, Kuwait; msalem@au.edu.kw

² College of Engineering and Petroleum, Kuwait University, Kuwait City 13060, Kuwait; ruqaya.alsabah@ku.edu.kw

³ Coastal Research Institute (CORI), National Water Research Center, Alexandria 21415, Egypt; mohamed_elnabwy@nwr.gov.eg

⁴ Civil Engineering Department, Faculty of Engineering, Damietta University, New Damietta 34518, Egypt

⁵ Department of Civil Engineering, College of Engineering, Qassim University, Buraydah 51452, Saudi Arabia; e.elbeltagi@qu.edu.sa

⁶ Department of Civil Engineering, Faculty of Engineering-Matara, Helwan University, Cairo 11718, Egypt

* Correspondence: mtantawy@m-eng.helwan.edu.eg

Abstract: This study explores the increasing adoption of virtual alternative dispute resolution (VADR) in the construction industry, enhancing efficiency and accessibility in dispute resolution. VADR is crucial for streamlining processes and reducing participation barriers. The study aims to investigate the critical success factors (CSFs) influencing the adoption of VADR in the construction sector. Given the rising importance of VADR technologies, understanding the key factors driving their acceptance is crucial. The background highlights the growing reliance on innovative technologies to boost operational efficiency and decision-making processes. The data for the study were collected using a cross-sectional design with online structured survey questionnaire (N = 97) from diversified construction industries. Using Smart PLS 4, structural equation modeling (SEM) was employed to test the validity, reliability, and proposed hypotheses of the study. The results showed that cost factors had the greatest impact on VADR acceptance, followed by user competence and training, procedural adaptability, and technological infrastructure. Logistical assistance and legal frameworks also had a considerable favorable impact. However, stakeholder buy-in had no significant influence on VADR implementation. The implications indicate that economic feasibility, logistical readiness, flexible procedures, supportive legal contexts, and user skills are significant factors for successful VADR integration. Governments and organizations should deploy VADR technologies to encourage innovation and operational improvement in the construction industry.

Keywords: critical success factors (CSFs); construction industry; virtual alternative dispute resolution (VADR); structural equation modeling (SEM); surveys; technology adoption



Citation: Salem, M.; Al-Sabah, R.S.; Elnabwy, M.T.; Elbeltagi, E.; Tantawy, M. Critical Success Factors for the Widespread Adoption of Virtual Alternative Dispute Resolution (VADR) in the Construction Industry: A Structural Equation Modeling Analysis. *Buildings* **2024**, *14*, 3033. <https://doi.org/10.3390/buildings14093033>

Academic Editor: Md Morshed Alam

Received: 11 August 2024

Revised: 14 September 2024

Accepted: 16 September 2024

Published: 23 September 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Virtual alternative dispute resolution (VADR) in the construction industry enhances dispute resolution by reducing costs, speeding up processes, and increasing accessibility. It enables the efficient handling of conflicts without the need for physical meetings. VADR is rapidly transforming industries like construction and education by improving training effectiveness and operational efficiency. The allocation of resources for VADR extends beyond monetary investments and encompasses the distribution of human resources, technological assets, and support services. Several intricately intertwined factors, including cost, logistical support, and technical infrastructure, affect the adoption rates and degree of integration of VADR technologies [1,2]. The research conducted by Exon and Lee [3]

demonstrated that virtual mediation can decrease expenses related to in-person dispute resolutions, such as travel and lodging costs for mediators and disputants, thereby augmenting its perceived worth. Alessa [4] emphasized the ease of use and convenience of VADR, especially in cases involving international disputes, where participants can avoid the complications of traveling across borders. Lingasabesan and Abenayake [5] emphasized the significance of providing ongoing support and updates to technology systems in order to preserve their effectiveness in the rapidly changing technological environment.

Initial investments and ongoing maintenance costs are frequently cited as major deterrents, highlighting significant research gaps in understanding how financial barriers affect the adoption of VADR. However, in-depth examinations of the cost thresholds that drive these choices are still rare, especially in understanding how these thresholds differ between industries [1,4]. Additionally, there has been insufficient research on logistical support, despite its critical role in the effective implementation and ongoing application of VADR technologies. Requirements such as supply chain dynamics, the availability of technical support, and maintenance services are crucial but frequently overlooked factors that guarantee the operational sustainability of these technologies [6,7]. Furthermore, thorough research on procedural adaptability or an organization's capacity to incorporate VADR into current workflows is lacking, raising concerns about the scalability and flexibility of these technologies across various organizational structures [6].

Research shows the growing role of VADR in construction, but there are still barriers to implementing VADR. Wang et al. [1] examined how VR improves construction engineering training and efficiency, laying the groundwork for VADR's potential impact on conflict resolution. Aboulata et al. [2] investigated construction project factors for choosing alternative dispute resolution methods, but they did not address the technological integration needed for VADR implementation. Gómez-Moreno [6] discussed remote arbitration communication but did not address the specific challenges of online dispute resolution unique to the construction industry. Scherer [7] provided an analytical framework for remote hearings in international arbitration, which could inform VADR protocols but did not address sector-specific disputes. Barnett and Treleven [8] found that while the potential of VADR has been understood, critical gaps remain, particularly in aligning virtual solutions with industry-specific requirements and integrating AI and blockchain technologies. In addition, Scherer's [7] arbitration hearing framework showed that remote proceedings reduce the need for costly physical meetings. Alessa [4] found that AI-based decision-making could greatly impact VADR system adaptability. Gómez-Moreno [6] noted that VADR regulatory and legal frameworks are underexplored without industry-specific examples. Case studies of VADR-resolved construction disputes under these frameworks would help explain its regulatory implications. Aboulata et al. [2] suggested studying how local regulatory structures affect VADR's construction implementation.

Regional variations exist in the impact of regulatory and legal frameworks on VADR adoption. Although specific studies have examined these influences, comprehensive comparative analyses are scarce. Depending on the regulatory landscape and industry-specific legal considerations, these frameworks may help or impede the integration of advanced technologies [8,9]. The importance of stakeholder buy-in is also underappreciated, and stakeholder perceptions significantly affect technology adoption strategies. However, studies frequently do not detail how these beliefs affect organizational decisions about implementing VADR technologies [10,11].

To address these gaps, this study aims to identify and analyze the critical success factors (CSFs) that govern the adoption of VADR technologies across different industries. By focusing on the intersection of procedural, regulatory, logistical, and economic aspects, this research seeks to elucidate how these factors influence the successful integration of VADR. Specifically, this study will (1) identify the CSFs governing VADR adoption by pinpointing the successful factors that influence the adoption of VADR technologies across different industries, (2) investigate the impact of these CSFs on VADR adoption by assessing how each identified success factor affects the adoption and integration of VADR

technologies, and (3) determine the most significant CSFs by evaluating and prioritizing the importance of these factors to identify which ones most significantly impact successful VADR implementation.

By addressing these objectives, this research aims to fill existing theoretical and practical gaps, providing a comprehensive framework for understanding the dynamics of VADR adoption. This enhanced understanding will be valuable for organizations and policymakers seeking to leverage VADR technologies effectively, ensuring their optimal utilization and fostering innovation in diverse professional settings.

2. Literature Review

The effectiveness of VADR adoption in the construction industry is underscored by several aspects. Key elements such as robust technical infrastructure, including reliable internet connectivity, platform compatibility, and cybersecurity, are essential for the smooth operation of VADR systems [4,12]. Universal platform operability ensures consistent user experiences across jurisdictions [11]. Additionally, user competence and continuous training are vital for effective participation, enhancing user engagement and system usability [3,5].

Compliance with legal standards and procedural adaptability are crucial for the legitimacy and trustworthiness of VADR systems [13]. Legal frameworks must ensure the validity and enforceability of VADR outcomes to build participant confidence [5]. The standardization across jurisdictions helps maintain consistency and reliability [14]. Adapting traditional dispute resolution methods to virtual settings and addressing logistical challenges, such as time zone management and equitable access to technology, are essential for improving participant engagement and satisfaction [15,16].

Furthermore, VADR improves accessibility and inclusivity by enabling remote participation, thus overcoming geographical barriers [1]. This inclusivity is further supported by continuous user training and support [11]. Technological integration, including artificial intelligence (AI) and virtual reality (VR), enhances the effectiveness of VADR by automating dispute resolution processes and improving participant engagement through realistic simulations [2,8]. VADR also contributes to environmental sustainability by reducing the need for travel and physical documentation, thus lowering the carbon footprint of dispute resolution processes [1,11].

Given these significant benefits, understanding the factors that influence the adoption of VADR in the construction industry is crucial. This section reviews the existing literature on these factors, highlighting their significance and impact on VADR adoption. By understanding these factors, stakeholders can better facilitate the integration of VADR, leading to improved operational efficiency and decision-making processes. The following are the critical factors affecting the adoption of VADR based on existing studies.

2.1. Technical Infrastructure

VADR adoption depends on robust technical infrastructure, including reliable internet connectivity to enable real-time interaction and avoid delays [1,5]. Poor internet quality can degrade VR experiences, leading to misunderstandings [1]. Blockchain technology (BCT) can enhance internet reliability by decentralizing data management [8]. Platform compatibility, supporting multiple operating systems and devices, is crucial for VADR [6,14]. Effective VADR also requires robust cybersecurity measures to protect data and privacy. AI-powered systems can enhance security by identifying and responding to threats in real time [4,11]. Holistic cybersecurity policies and practices are essential for maintaining system integrity [17]. In addition, Garon [14] emphasized the need to harmonize virtual platforms with legal frameworks to make VADR systems technologically compatible and compliant with various jurisdictions. According to Exon and Lee [3], online mediation's effectiveness depends on platform usability and accessibility.

2.2. User Competence and Training

VADR success hinges on user competence and training, which ensure effective and confident platform use. Participants need familiarity with necessary technologies and processes to reduce anxiety and resistance, thus fostering confidence [13]. Understanding virtual environments is crucial for complex negotiations [14], and technology familiarity enhances trust in the process [12]. Effective VADR adoption requires well-designed training programs that cover platform technology and procedural knowledge [15]. Practical experience is essential, as theoretical knowledge alone is insufficient [16]. Ongoing support, including AI-driven tools for real-time assistance and responsive helpdesks, ensures that users receive the necessary help and can share best practices through forums [6,12].

Technical experience is crucial in training programs, as theoretical knowledge alone cannot prepare participants for real disputes [16]. Maintaining VADR platforms requires ongoing support including technical assistance, user education, and platform improvement. Zeleznikow [12] discussed how AI-driven tools can provide real-time support and predictive assistance to help users navigate the system and avoid common errors.

2.3. Regulatory and Legal Framework

An effective regulatory and legal framework is crucial for the widespread adoption of VADR, addressing compliance, validity and enforceability, and standardization. Compliance with relevant laws and regulations ensures VADR system integration and acceptance [5,14]. VADR systems must adhere to international standards and have verifiable and auditable frameworks [6,7]. Legal frameworks must ensure the enforceability of decisions made in virtual environments to build trust [3,18]. BCT can enhance enforceability by securely documenting decisions [8]. AI can help standardize and customize dispute resolution, ensuring consistency across different legal systems [12]. Standardizing procedures aids in transparent and robust decision-making [1,19].

2.4. Procedural Adaptability

Successful VADR implementation requires a robust procedural adaptability framework to transition traditional dispute resolution methods to virtual environments effectively [14]. This involves rethinking procedures for the virtual setting, not just transferring them online, and adapting courtroom protocols to maintain decorum and fairness [16]. Effective virtual communication is crucial for presenting arguments and evidence, with AI enhancing clarity [1,4]. Technologies like telepresence can improve mediator efficiency and participant satisfaction [3]. Blockchain technology (BCT) ensures the verification and authenticity of digital evidence [6]. Additionally, AI aids in virtual cross-examinations and document authentication, meeting legal criteria for enforceable results [12,20].

2.5. Logistical Support

Robust logistical support is essential for widespread VADR adoption, addressing challenges such as time zone management, technology access, and participant engagement. Effective global participation requires scheduling flexibility to accommodate different time zones, enhancing VADR accessibility [14,16]. BCT can help manage time zone differences by securely storing procedural actions with timestamps [8]. Equitable technology access is crucial, particularly in developing regions, necessitating targeted investments and affordable solutions [5]. Providing subsidized or loaned equipment to underprivileged parties can enhance fairness [20]. Innovations like low-bandwidth solutions increase platform accessibility [11]. Lastly, maintaining updated technology platforms ensures that they accommodate various user abilities.

2.6. Stakeholder Buy-In

Stakeholder buy-in is essential for VADR adoption, requiring support from key stakeholders, perceived value, and active promotion. Legal professionals, judiciary members, technology providers, and end-users must back VADR [14]. Industry-specific endorse-

ments, especially from the construction sector, are crucial [5]. Educational institutions and professional development programs play a vital role in preparing future legal professionals for virtual environments [1]. Training programs and certifications in VADR standardize practices, enhance technology reliability, and increase outcome predictability [6]. Efforts to promote and advocate for VADR further support its widespread acceptance and implementation.

2.7. Cost Considerations

Implementing VADR on a large scale involves significant cost factors, including initial investments, ongoing expenses, and resource allocation. Initial investments cover technological infrastructure, software licenses, and security measures [1,8]. Strategic planning in distributing these investments ensures efficient resource use, integrating user-friendly interfaces and training modules to save costs in the long term [5]. Ongoing expenses include maintenance, updates, and administrative costs, requiring continuous support to maintain system effectiveness [3,5]. Resource allocation extends to human resources and technological assets, emphasizing training and support for mediators and legal professionals [7,12]. Investments in research and development further enhance VADR's efficiency and outcomes [20].

In conclusion, the adoption of VADR in the construction industry is influenced by various factors, including technical infrastructure, user competence and training, regulatory and legal frameworks, procedural adaptability, logistical support, participant engagement, stakeholder buy-in, perceived value, promotion and advocacy, and cost considerations. Each of these factors plays a significant role in determining the effectiveness of VADR adoption. Table 1 provides a summary of these CSFs and their key insights from the literature.

Table 1. Summary of the CSFs in the adoption of VADR.

Critical Success Factors	Sub-Factors	Key Insights from the Literature
Technical Infrastructure (TI)	Internet Reliability (TI1)	Essential for effective operation and interaction [1].
	Platform Compatibility (TI2)	Need for universal platform operability [21].
	Cybersecurity Measures (TI3)	Importance of robust security to protect data and ensure privacy [4].
User Competence and Training (UCT)	Participant Familiarity (UCT1)	Familiarity enhances user engagement and system usability [3].
	Training Programs (UCT2)	Training programs necessary for skill development [6].
	Ongoing Support (UCT3)	Continuous support improves proficiency and system adaptability [12].
Regulatory and Legal Framework (RLF)	Compliance (RLF1)	Must comply with existing legal standards [5].
	Validity and Enforceability (RLF2)	Ensuring outcomes are legally recognized [18].
	Standardization (RLF3)	Crucial for maintaining consistency across jurisdictions [14].
Procedural Adaptability (PA)	Transition of Traditional Methods (PA1)	Adapting traditional methods to virtual settings [15].
	Virtual Communication (PA2)	Ensuring clear and effective communication [3].
	Cross-examination and Authentication (PA3)	Authenticating identities and evidence in a virtual environment [6].

Table 1. *Cont.*

Critical Success Factors	Sub-Factors	Key Insights from the Literature
Logistical Support (LS)	Time Zone Management (LS1)	Coordinating sessions across different time zones [16].
	Technology Access (LS2)	Ensuring equitable access to necessary technology [5].
	Participant Engagement (LS3)	Keeping participants actively involved and interested [3].
Stakeholder Buy-In (SB)	Support from Key Stakeholders (SB1)	Gaining support from legal and technical professionals [14].
	Support from Key Stakeholders (SB2)	Demonstrating cost-effectiveness and efficiency [8].
	Promotion and Advocacy (SB3)	Using success stories and strategic partnerships for promotion [16].
Cost Considerations (CCs)	Initial Investment (CC1)	Upfront costs for technology and training [1].
	Ongoing Expenses (CC2)	Recurring costs of maintenance and updates [3].
	Resource Allocation (CC3)	Efficient use of financial and human resources [20].

3. Research Methodology

3.1. Research Design

This study uses quantitative research methodology to identify and analyze CSFs for adopting VADR in the construction industry. Initially, a thorough literature review identified key factors which formed the basis for a pilot questionnaire. Feedback from expert interviews refined the questionnaire, which was then distributed via LinkedIn and directly to industry experts. The collected data were cleaned, removing incomplete and irrelevant responses. The cleaned data were analyzed using SEM through Smart PLS 4 to test validity, reliability, and the proposed hypotheses. Ethical considerations, including confidentiality, were maintained throughout.

3.2. Data Collection and Procedures

The data collection process was meticulously planned to ensure a representative sample of industry experts. Initially, a refined questionnaire was developed based on CSFs identified through the literature review and expert interviews. To ensure clarity and relevance, the questionnaire was pre-tested and enhanced via a pilot survey involving experienced construction dispute resolution stakeholders. A comprehensive literature review on VADR adoption CSFs informed the pilot questionnaire's constructs. To ensure clarity and relevance, a small group of industry professionals tested it. VADR and construction experts provided content validity, question phrasing, and response scale accuracy feedback. Their feedback helped clarify and align the study's objectives. Before release, the final version was refined and validated. The questionnaire covered VADR-related topics, including demographic information, organization type, participant role, construction industry experience, and engagement with alternate dispute resolutions (ADRs). For this pilot study, six industrial stakeholders were approached, and their opinions were solicited about the survey. Feedback and comments were received on the survey items. Later, the survey items were revised to produce a final survey. Likert-scale questions assessed the various CSFs identified in Table 1.

The questionnaire was sent to construction professionals via LinkedIn and email. LinkedIn leveraged industry networks to reach a broad and relevant audience, while email was more personal and direct. Together, these methods produced a representative sample of respondents. Professionals with VADR adoption experience were optimally involved. A convenience sampling technique targeted stakeholders from project management, consultancy, and contracting organizations, as well as ADR and VADR professionals. Data

collection spanned two months, with periodic reminders sent to encourage participation. The data cleaning process involved identifying and removing incomplete or irrelevant responses. Responses with missing data in key variables and inconsistent answers were excluded from the dataset. Outliers were identified using statistical methods and discarded to maintain the integrity of the analysis. Duplicate responses were removed. After the data cleaning process, 97 valid responses remained from the 117 collected, which is considered sufficient for further SEM analysis [22]. Furthermore, it has been reported that a sample size ranging from 50 to 500 is appropriate for bootstrapping in structural equation modeling (SEM) analysis [23,24]. Therefore, the study targeted 117 respondents from the construction industry. By leveraging LinkedIn and direct email distribution, the study effectively reached a broad and relevant audience, ensuring robust and representative data on the CSFs for VADR adoption.

3.3. Data Analysis

Due to its ability to handle small sample sizes, non-normal data, and complex models, Smart PLS-SEM was chosen over CB-SEM. Hair et al. [25] recommend PLS-SEM for exploratory research models that focus on prediction rather than theory testing. PLS-SEM is also more flexible when working with real-world datasets that do not meet strict normality assumptions [26]. Memon et al. [26] also recommend Smart PLS for studies that maximize explained variance and handle formative constructs. Smart PLS also bootstraps path coefficient significance, making it ideal for exploratory hypothesis testing [27].

4. Findings of the Study

4.1. Demographics Analysis

The demographics analysis, as shown in Table 2 and Figure 1, reveals a balanced distribution across organization types, with large corporates representing 38.1%, small businesses 32%, and medium-sized enterprises 29.9%. Middle management had the highest participation rate at 36.1%, indicating their significant role in industry practice implementation and evaluation. A notable portion of participants (35.1%) reported having 11–20 years of construction industry experience, suggesting a mature and knowledgeable sample. This experienced cohort, primarily consisting of senior and middle managers, is likely to provide valuable insights into the construction industry's dynamics and challenges. The diverse distribution across organization types and levels of experience underscores the study's robustness and enhances its validity and applicability to the industry demographic data.

Table 2. Demographic analysis.

Demographics	Categories	Number	%
Organization type	Large Corporation	37	38.1%
	Medium-sized Enterprise	29	29.9%
	Small Business	31	32.0%
Participants' role	Senior Management	20	20.6%
	Middle Management	35	36.1%
	Technical Staff	25	25.8%
	Administrative Staff	17	17.5%
Participants' experience in construction industry	Less than 5 years	18	18.6%
	5–10 years	25	25.8%
	11–20 years	34	35.1%
	More than 20 years	20	20.5%

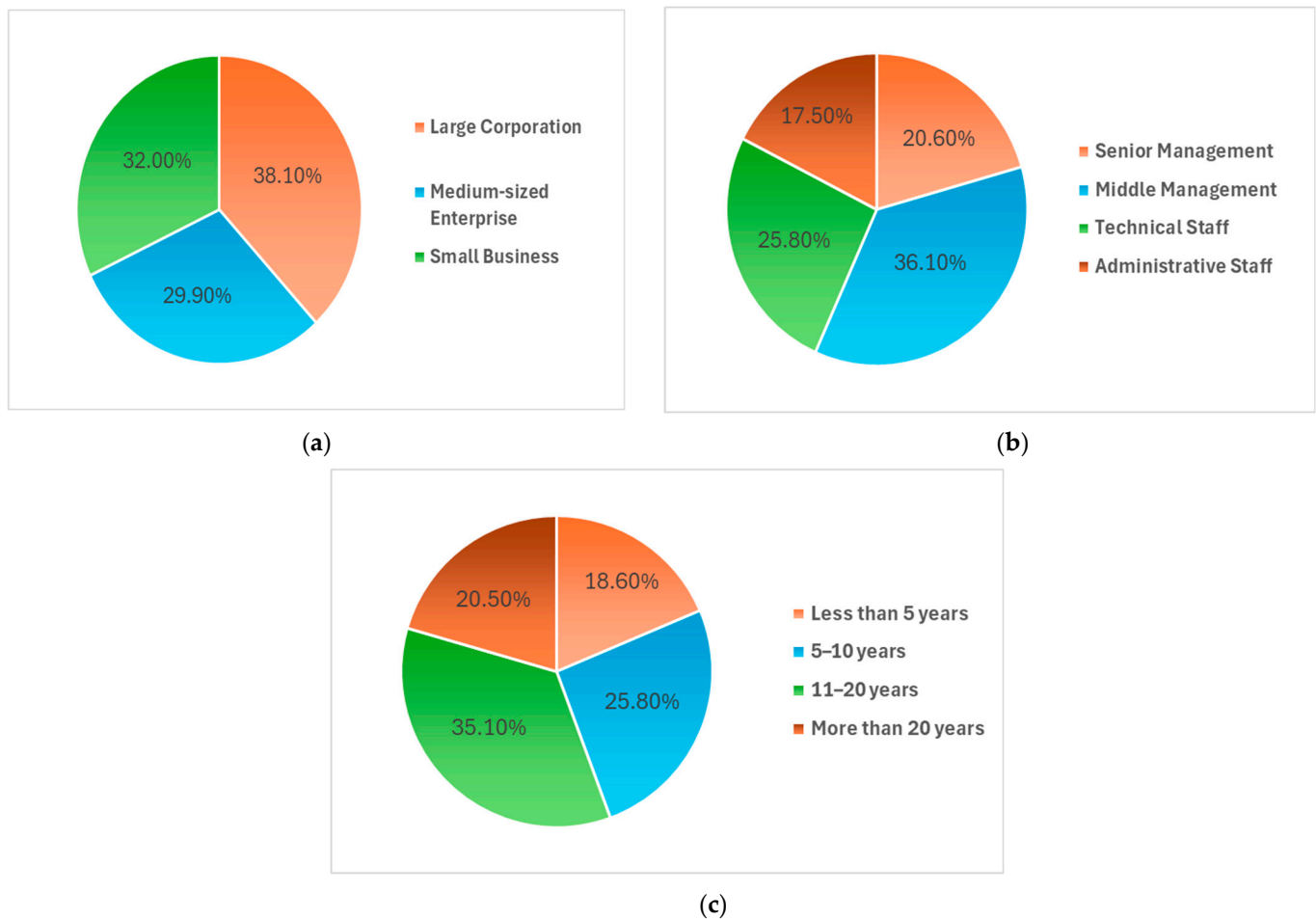


Figure 1. Demographic analysis. (a) Organization type. (b) Participant role. (c) Participants' experience in the construction industry.

4.2. Structural Equation Modeling

There are two approaches for SEM: component-based and covariance approaches. Memon [26] stated that the component-based approach (PLS-SEM) is better suited for predictive purposes than the covariance-based approach (CB-SEM), given the fact that it is a more powerful statistical tool for assessing various parameters and reinvesting in experimental variance. The main objective of this study is to test and verify a theoretical model from a forecasting perspective. It is, furthermore, assessing the underlying relationships between various CSFs and enablers. Therefore, PLS-SEM proved valuable for this study; the model created appears in Figure 2.

To effectively utilize SEM, it is essential to develop two interconnected models: (1) the measurement model and (2) the structural model. The measurement model is crucial as it evaluates how latent constructs and their observable indicators relate to one another, ensuring that the constructs are measured accurately. A latent construct is the continuous variable, and its indicators are survey items asked for each latent construct. The structural model, on the other hand, examines the relationships between the latent constructs themselves, providing insights into the causal relationships within the theoretical framework. Both models are necessary to comprehensively evaluate the data and validate the theoretical constructs. Each of these models will be discussed in the subsequent sections.

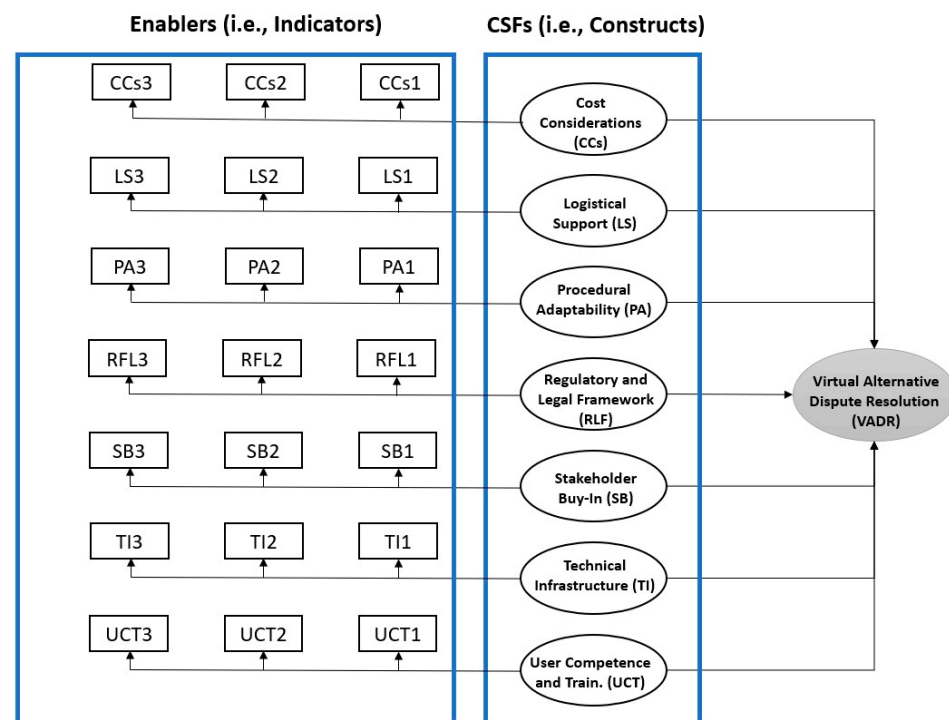


Figure 2. SEM model.

4.2.1. Measurement Model

The measurement model assesses how latent constructs and their observed indicators relate to one another. The next subsections detail the processes and statistical tests used to evaluate the measurement model's validity and reliability, specifically focusing on convergent and discriminant validity.

Convergent Validity

Outer Loadings: Outer loadings in reflective measurement models indicate the strength of the relationship between each indicator and its corresponding construct, reflecting the extent to which each indicator effectively measures its construct [25]. An indicator with an outer loading value of 0.4 or higher is considered acceptable [26,28]. In this study, all indicators surpassed the required threshold, demonstrating strong and reliable contributions to their respective constructs. As shown in Table 3, all indicators exceeded the 0.4 threshold and were therefore deemed acceptable.

Cronbach's Alpha (α): Cronbach's alpha coefficient assesses the internal consistency of a set of items by determining how effectively they measure a specific construct [25]. The threshold for acceptable reliability is a Cronbach's alpha value larger than 0.7 [27]. All of the study's constructs, as shown in Table 3, either reached or were beyond the necessary Cronbach's alpha threshold, indicating good internal consistency. Cost considerations as well as other measurement constructs had good factor loadings, Cronbach's alpha, and composite reliability. Therefore, all constructs were considered reliable.

Composite Reliability (CR): Composite reliability is regarded as a measure of internal consistency that is more accurate than Cronbach's alpha, as it accounts for the varying contributions of individual items [28]. The threshold for composite reliability is also 0.7 [27]. All constructs in this study achieved composite reliability values above this threshold, as shown in Table 3, indicating high reliability and internal consistency across the scales.

Table 3. Construct reliability and convergent validity tests.

Scales	Items	Outer Loadings	α	CR	AVE	Full Collinearity
Cost Considerations (CCs)	CC1	0.855	0.826	0.827	0.743	3.100
	CC2	0.896				
	CC3	0.832				
Logistical Support (LS)	LS1	0.704	0.720	0.739	0.510	2.417
	LS2	0.779				
	LS3	0.747				
Procedural Adaptability (PA)	PA1	0.745	0.718	0.715	0.569	2.272
	PA2	0.883				
	PA3	0.777				
Regulatory and Legal Framework (RLF)	RLF1	0.740	0.748	0.750	0.586	2.556
	RLF2	0.765				
	RLF3	0.791				
Stakeholder Buy-In (SB)	SB1	0.732	0.741	0.795	0.562	1.124
	SB2	0.827				
	SB3	0.705				
Technical Infrastructure (TI)	TI1	0.705	0.737	0.764	0.574	1.727
	TI2	0.821				
	TI3	0.744				
User Competence and Training (UCT)	UCT1	0.728	0.702	0.728	0.559	3.211
	UCT2	0.823				
	UCT3	0.778				
Overall VADR Adoption	VADRA1	0.720	0.794	0.913	0.678	3.123
	VADRA2	0.756				
	VADRA3	0.718				
	VADRA4	0.717				
	VADRA5	0.741				

Average Variance Extracted (AVE): AVE assesses the convergent validity of latent constructs, measuring the amount of variance captured by a construct relative to the variance due to measurement error [27]. An AVE value above 0.5 indicates that the construct explains more than half of the variance of its indicators [28]. As demonstrated in Table 3, all constructs in this study have AVE values exceeding the 0.5 threshold, confirming good convergent validity. These results demonstrate the internal consistency and convergence of the analytical model, with each construct adequately evaluated. Furthermore, high external loadings for the constructs suggest strong correlations and relationships between the relevant elements, reinforcing the robustness of the model.

Discriminant Validity

Fornell and Larcker [29] criterion: The criterion developed by Fornell and Larcker [29] assesses the degree of correlation that exists between the construct and its AVE square root. The AVE square root for every latent variable (i.e., construct) must be higher than the corresponding construct correlation value [29,30]. The Fornell–Larcker criterion for discriminant validity in structural equation modeling requires that each construct’s square root of the AVE be greater than its correlations with other constructs [27]. Based on the matrix, all constructs met this criterion: cost considerations (0.862) surpass their highest correlation with user competence and training (0.861), logistic support (0.714) surpasses regulatory and legal framework (0.684), and procedural adaptability (0.790) surpasses regulatory and legal framework (0.679). Regulatory and legal framework AVE (0.766) surpasses its correlations, stakeholder buy-in (0.679) surpasses its highest correlation of 0.251 with logistic support, technical infrastructure (0.758), and user competence and training (0.948) significantly surpass their correlations, and VADR adoption (0.896) surpasses its highest correlation of 0.846 with cost considerations. This shows that each construct uniquely captures indicator variance and is distinct from other constructs in the model,

demonstrating robust discriminant validity. Table 4 displays the outcomes of the Fornell and Larcker criterion [29].

Table 4. Correlation of latent variables and discriminant validity (Fornell–Larcker).

Constructs	CC	LS	PA	RLF	SB	TI	UCT	VADR Adoption
CCs	0.862							
LS	0.574	0.714						
PA	0.491	0.570	0.790					
RLF	0.449	0.684	0.679	0.766				
SB	0.242	0.251	0.193	0.082	0.679			
TI	0.526	0.511	0.521	0.450	0.205	0.758		
UCT	0.861	0.619	0.608	0.555	0.221	0.607	0.948	
VADR Adoption	0.846	0.678	0.773	0.739	0.356	0.723	0.896	0.527

Note: CCs = cost considerations; 1 = logistic support; 3 = procedural adaptability; 4 = regulatory and legal framework; 5 = stakeholder buy-in; 6 = technical infrastructure; 7 = user competence and training; 8 = virtual alternative dispute resolution.

Cross-loading criterion: The loading value of any indicator with its construct must be greater than the loading value of every other construct on the same row, according to the cross-loading condition [29]. The matrix showing construct–indicator cross-loadings is essential for assessing the SEM discriminant validity. Indicators that load more on their constructs than others support discriminant validity. The indicators for cost considerations (0.86, 0.90, 0.83) have the highest loadings on their own construct and the highest cross-loading at 0.82 on UCT3, confirming strong discriminant validity. Like procedural adaptability, regulatory and legal framework, stakeholder buy-in, technical infrastructure, and user competence and training, the logistic support indicators (0.60, 0.78, 0.75) have stronger loadings on their intended construct than their cross-loadings. This pattern shows that each construct uniquely captures the variance of its own indicators, distinguishing it from other constructs, which is essential for model integrity and good discriminant validity. Table 5 displays the cross-loading criterion findings. The fundamental unidimensional degree of each construct is demonstrated by the loading values of the constructs being higher than the loading values of the other constructs on the same row.

Table 5. Cross-loadings to test the discriminant validity of indicators.

Constructs/Indicators	CCs	LS	PA	RLF	SB	TI	UCT	VADR Adoption
CC1	0.86	0.39	0.34	0.29	0.28	0.53	0.68	0.69
CC2	0.90	0.51	0.40	0.38	0.20	0.44	0.72	0.72
CC3	0.83	0.57	0.51	0.48	0.15	0.40	0.82	0.77
LS1	0.32	0.60	0.25	0.40	0.25	0.27	0.32	0.45
LS2	0.54	0.78	0.54	0.49	0.16	0.47	0.56	0.66
LS3	0.34	0.75	0.38	0.58	0.15	0.33	0.41	0.55
PA1	(0.26)	(0.08)	(0.14)	(0.01)	(0.38)	(0.01)	(0.23)	(0.22)
PA2	0.46	0.45	0.88	0.56	0.11	0.51	0.56	0.68
PA3	0.28	0.51	0.78	0.61	0.09	0.37	0.39	0.56
RLF1	0.24	0.47	0.58	0.74	(0.01)	0.31	0.34	0.52
RLF2	0.37	0.54	0.42	0.76	0.22	0.41	0.45	0.59
RLF3	0.41	0.55	0.57	0.79	(0.03)	0.31	0.47	0.59
SB1	(0.17)	(0.08)	(0.14)	(0.11)	(0.73)	(0.13)	(0.17)	(0.25)
SB2	(0.21)	(0.29)	(0.17)	(0.04)	(0.83)	(0.19)	(0.18)	(0.31)
SB3	0.02	0.03	0.03	0.14	(0.41)	0.04	0.04	(0.01)
TI1	0.31	0.40	0.28	0.33	0.17	0.70	0.38	0.47
TI2	0.55	0.51	0.50	0.39	0.20	0.82	0.58	0.68
TI3	0.28	0.21	0.37	0.30	0.08	0.74	0.38	0.45

Table 5. Cont.

Constructs/Indicators	CCs	LS	PA	RLF	SB	TI	UCT	VADR Adoption
UCT1	0.36	0.41	0.40	0.45	(0.02)	0.55	0.63	0.54
UCT2	0.83	0.57	0.51	0.48	0.15	0.40	0.82	0.77
UCT3	0.68	0.39	0.44	0.33	0.34	0.45	0.78	0.68

Note: CCs = cost considerations; 1 = logistic support; 3 = procedural adaptability; 4 = regulatory and legal framework; 5 = stakeholder buy-in; 6 = technical infrastructure; 7 = user competence and training; 8 = virtual alternative dispute resolution.

4.2.2. Structural Model (Path Analysis)

The structural model, also known as path analysis, examines the relationships between the constructs in the model. The significance of these relationships is determined by evaluating the path coefficients (β -values) and p -values.

Significance of path coefficients using the β -Value: The β -value coefficient describes the strength and direction of the association between constructs [26].

Table 6 and Figure 3 show that the leading path coefficient is for cost considerations with a β -value of 0.282, indicating a strong influence on VADR adoption. The constructs are ranked in descending order of their β -values as follows: user competence and training ($\beta = 0.225$), procedural adaptability ($\beta = 0.186$), regulatory and legal framework ($\beta = 0.177$), Technical Infrastructure ($\beta = 0.161$), logistical support ($\beta = 0.149$), and stakeholder buy-in (SB) ($\beta = 0.117$).

Table 6. Path analysis.

Paths	β Values	p Values	VIF
CC $\rightarrow$ VADR Adoption	0.282	0.00	4.100
LS $\rightarrow$ VADR Adoption	0.149	0.00	2.417
PA $\rightarrow$ VADR Adoption	0.186	0.00	2.272
RLF $\rightarrow$ VADR Adoption	0.177	0.00	2.556
SB $\rightarrow$ VADR Adoption	0.117	0.293	1.124
TI $\rightarrow$ VADR Adoption	0.161	0.00	1.727
UCT $\rightarrow$ VADR Adoption	0.225	0.00	5.211

Note: CC: cost considerations; LS: logistic support; PA: procedural adaptability; RLF: regulatory and legal framework; SB: stakeholder buy-in; TI: technical infrastructure; UCT: user competence and training.

Significance of path coefficients using the p -value: The statistical significance of the correlations between constructs is ascertained by the p -value [26,28]. p -values of less than 0.05 for path coefficients are regarded as statistically significant [27]. The correlations between the constructs are substantial and impactful, as evidenced by the path coefficients with p -values less than or equal to 0.05, as presented in Tables 3 and 6. Specifically, the p -values are all 0.00, except for stakeholder buy-in which has a p -value of 0.293, indicating that its relationship with VADR adoption is not statistically significant.

Variance inflation factor (VIF): The degree of collinearity between the formative elements of the constructs in the model is ascertained by the variance inflation factor, or VIF. The VIF cut-off level is ≤ 5 [26,28]. Table 6 illustrates that every construct met the VIF threshold value of <5 , suggesting that the subdomains independently contribute to the higher-order construct inside the model.

Explanatory power (R^2 value): The explanatory power is a measure of how well the model can explain the variation of the dependent variable [26]. The smart-PLS algorithm technique is used to calculate the R^2 value. VADR adoption, the study's main dependent variable, has an adjusted R^2 value of 0.992. This shows that the seven independent variables explain 99.2% of the variance in VADR adoption, meaning that the seven latent variables in the model were responsible for 99.2% of the variation in VADR adoption.

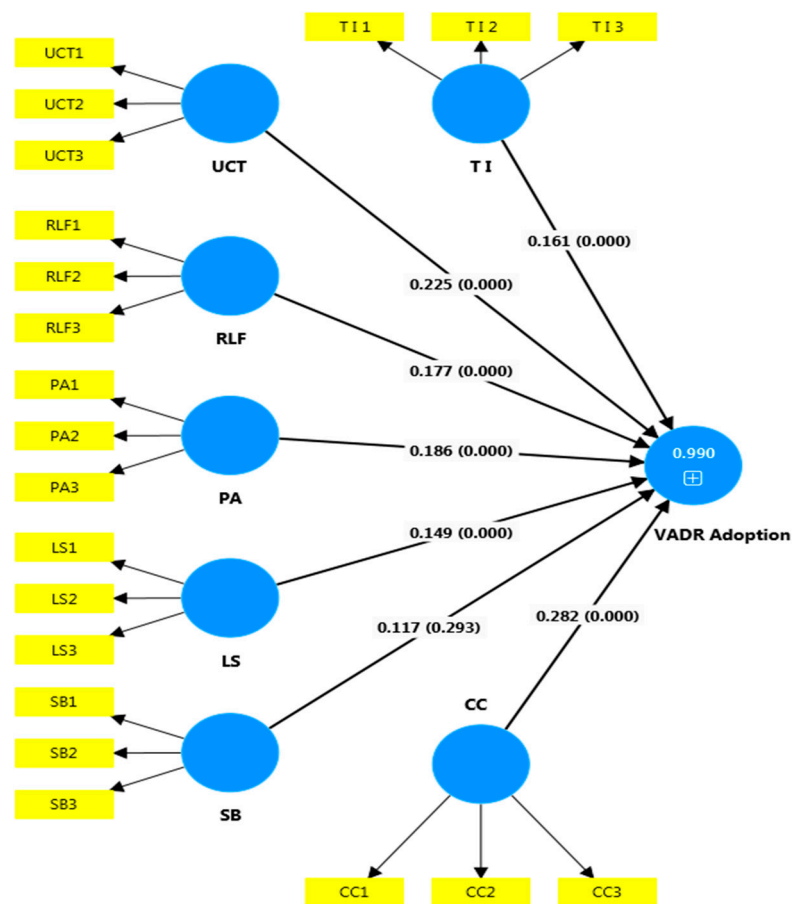


Figure 3. Structural model PLS-SEM (β -values and p -values). Note: CC = cost considerations; 1 = logistic support; 3 = procedural adaptability; 4 = regulatory and legal framework; 5 = stakeholder buy-in; 6 = technical infrastructure; 7 = user competence and training; 8 = virtual alternative dispute resolution.

5. Discussion

The adoption of VADR technologies in the construction industry is influenced by various CSFs. This study has identified and analyzed these factors using SEM to provide a comprehensive understanding of their impact on VADR adoption. The following discussion is based on the analysis results, shown in Figure 4, focusing on the significant CSFs: cost considerations, logistical support, procedural adaptability, regulatory and legal frameworks, technical infrastructure, and user competence and training.

Cost considerations emerged as the most influential factor affecting VADR adoption, with a β -value of 0.282. This indicates that financial feasibility is paramount in decision-making processes regarding VADR implementation. The findings are consistent with previous studies that highlight the importance of economic factors in technology adoption in the construction industry. Addressing cost-related concerns by providing clear ROI analyses and cost-saving benefits can enhance the adoption rates of VADR. Logistical support significantly impacts VADR adoption, reflected by a β -value of 0.149. Effective logistical frameworks, including robust supply chains, technical support, and maintenance services, are crucial for the sustainable implementation of VADR technologies. This aligns with existing research emphasizing the need for logistical readiness to ensure the smooth operation and maintenance of new technologies.

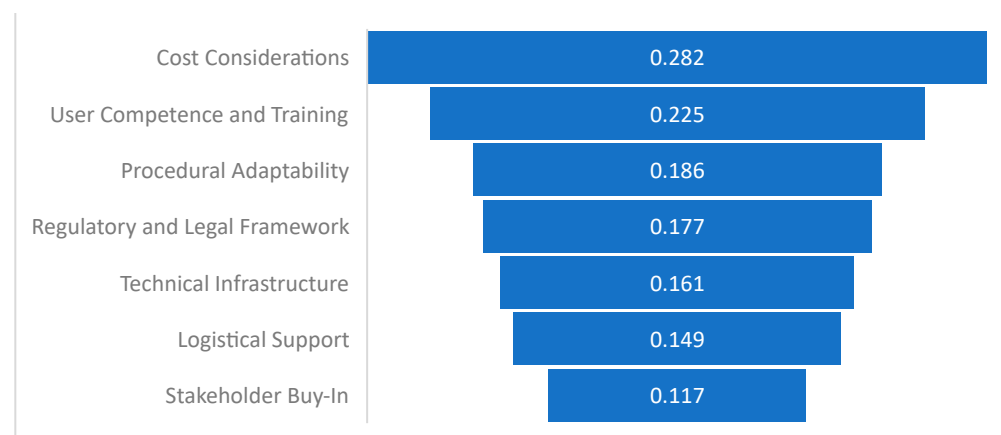


Figure 4. Path analysis— β -value.

Procedural adaptability, with a β -value of 0.186, indicates that the ability of organizations to integrate VADR into existing workflows is critical for its adoption. Organizations must develop flexible procedures that can accommodate the unique requirements of VADR, ensuring that traditional dispute resolution methods are effectively transitioned to virtual platforms. The regulatory and legal frameworks also play a significant role in VADR adoption, with a β -value of 0.177. Ensuring compliance with legal standards and creating supportive regulatory environments are essential for building trust and legitimacy in VADR systems. Standardizing legal frameworks across jurisdictions can facilitate the broader acceptance and implementation of VADR.

Technical infrastructure, with a β -value of 0.161, highlights the necessity of having reliable and advanced technological systems to support VADR. This includes ensuring robust internet connectivity, cybersecurity measures, and platform compatibility. The effectiveness of VADR is heavily dependent on the technical infrastructure's capacity to support seamless and secure virtual interactions.

User competence and training, with a β -value of 0.225, are critical for successful VADR adoption. Training programs that enhance users' technological skills and familiarity with VADR processes are essential. Continuous support and practical training can reduce resistance and increase confidence among users, thereby facilitating the effective use of VADR. Interestingly, stakeholder buy-in did not exhibit a significant impact on VADR adoption (β -value of 0.117 and p -value of 0.293). This suggests that while stakeholder support is important, it may not be as critical as the other factors analyzed. Further research could explore the nuances of stakeholder influence and identify strategies to enhance stakeholder engagement in the adoption of VADR.

The findings are consistent with those of Aboulata et al. [2], highlighting that cost-effectiveness is crucial to the construction industry's adoption of VADR. Logistical support boosts VADR adoption, proving that VADR technology integration requires strong logistical frameworks. In addition, Avramovic et al. [30] also stressed the importance of logistics in healthcare technology deployment. The findings are also consistent with the findings of Behfar et al. [10], who stressed adaptability in conflict resolution and team outcomes. The regulatory and legal framework, emphasizing the need for technology-friendly laws, also affects VADR adoption. Hence, Lingasabesan and Abenayake [5] explored the problems of regulatory frameworks and their potential in the construction sector's implementation of virtual alternative dispute resolution. Compared to Exon and Lee [3], who found that stakeholder engagement is essential to creating confidence and acceptance in online dispute resolution systems, stakeholder buy-in did not significantly influence VADR adoption. Wang et al. [1] noted that robust technical assistance is essential for the successful deployment of virtual reality systems in construction engineering education. User competence and training substantially affect VADR adoption, emphasizing the need for skill development and user preparation for new technologies. This supports Barnett

and Treleaven [8], who underlined the importance of training and expertise in AI and blockchain conflict resolution.

6. Conclusions

This study provides a comprehensive analysis of the CSFs influencing the adoption of VADR technologies within the construction industry, employing SEM to validate the theoretical model. The research identifies several key CSFs, including cost considerations, logistical support, procedural adaptability, regulatory and legal frameworks, technical infrastructure, and user competence and training. Among these, cost considerations and user competence and training emerged as the most significant, underscoring the necessity for detailed financial assessments and robust training programs to facilitate successful VADR implementation. This study also highlights the critical role of logistical support systems, such as reliable technical support and maintenance services, which are essential for the smooth operation and sustainability of VADR technologies. Procedural adaptability is another crucial factor, necessitating that organizations adjust their existing dispute resolution processes to seamlessly incorporate VADR. Additionally, this research emphasizes the importance of adhering to legal standards and advocating for standardized regulatory frameworks to facilitate broader VADR adoption. Investing in advanced technological infrastructure, including reliable internet connectivity and robust cybersecurity measures, is also vital for the effective functioning of VADR systems.

Despite its contributions, this study is limited by its focus on the construction industry, which may not fully capture the diverse challenges and opportunities associated with VADR technologies in other sectors. The cross-sectional design of this study also restricts insights into the long-term effectiveness and sustainability of VADR adoption. Future research should address these limitations by incorporating longitudinal studies to assess the enduring impacts of VADR technologies, exploring stakeholder engagement strategies to enhance support and buy-in, and conducting comparative analyses across different regions and sectors to identify best practices and sector-specific challenges.

Cost and user competence are the biggest CSFs affecting construction industry VADR adoption, according to this study. Successful VADR implementation depends on logistical support, procedural adaptability, regulatory frameworks, and technical infrastructure. The interaction between these CSFs emphasizes the need for organizations to balance financial investment with comprehensive training, reliable infrastructure, and flexible workflows. Standardized regulations and legal compliance boost VADR system sustainability. The framework for understanding VADR adoption in construction provides valuable insights for academic research and industry practices. The findings could help policymakers and organizations improve VADR strategies, increase adoption, and improve dispute resolution efficiency by identifying key drivers and barriers. To make VADR technologies applicable across industries, future research should examine sector-specific challenges and long-term effects.

Author Contributions: Conceptualization, M.T.; methodology, M.T.E., M.S. and M.T.; software, M.T.E., validation, M.T., M.S., M.T.E. and E.E.; formal analysis, M.T.E.; investigation, M.T., M.S., R.S.A.-S. and M.T.E.; resources, M.T., M.S. and M.T.E.; data curation, M.T. and R.S.A.-S.; writing—original draft preparation, M.T., M.S., M.T.E. and E.E.; writing—review and editing, M.T., M.S., M.T.E. and E.E.; visualization, M.T.E., M.S. and R.S.A.-S.; supervision, M.S. and E.E.; project administration, M.S. and R.S.A.-S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Wang, P.; Wu, P.; Wang, J.; Chi, H.-L.; Wang, X. A Critical Review of the Use of Virtual Reality in Construction Engineering Education and Training. *Int. J. Environ. Res. Public Health* **2018**, *15*, 1204. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Aboulata, H.K.; Younis, A.A.; Bakhoum, E.S. Assessment of Key Factors Affecting the Choice of Alternative Dispute Resolution Methods in Construction Projects. In Proceedings of the International Conference on Sustainable Construction and Project Management, Cairo, Egypt, 13–15 December 2023.
3. Exon, S.N.; Lee, S. Building Trust Online: The Realities of Telepresence for Mediators Engaged in Online Dispute Resolution. *Stetson Law Rev.* **2019**, *49*, 109.
4. Alessa, H. The Role of Artificial Intelligence in Online Dispute Resolution: A Brief and Critical Overview. *Inf. Commun. Technol. Law* **2022**, *31*, 319–342. [\[CrossRef\]](#)
5. Lingasabesan, V.; Abenayake, M. Opportunities and Challenges in Conducting Virtual Alternative Dispute Resolution (ADR) Methods in the Sri Lankan Construction Industry. In Proceedings of the 10th World Construction Symposium, Colombo, Sri Lanka, 24–26 June 2022; pp. 657–667. [\[CrossRef\]](#)
6. Gómez-Moreno, J.P. Advocacy for Online Proceedings: Features of the Digital World and Their Role in How Communication is Shaped in Remote International Arbitration. *Int. J. Semiot. Law* **2024**, *37*, 865–885. [\[CrossRef\]](#)
7. Scherer, M. Remote Hearings in International Arbitration: An Analytical Framework. *J. Int. Arbitr.* **2020**, *37*, 407–448. [\[CrossRef\]](#)
8. Barnett, J.; Treleven, P. Algorithmic Dispute Resolution—The Automation of Professional Dispute Resolution Using AI and Blockchain Technologies. *Comput. J.* **2018**, *61*, 399–408. [\[CrossRef\]](#)
9. Carrasco Delgado, M.O.; Juárez Landín, C.; Mendoza Pérez, M.A.; García Ibarra, J.R.S. Prototipo de un Simulador Virtual para la Enseñanza-Aprendizaje de los Medios Alternos de Solución de Conflictos (MASC) en México. *Religación. Rev. Cienc. Soc. Humanid.* **2023**, *8*, e2301014. [\[CrossRef\]](#)
10. Behfar, K.J.; Peterson, R.S.; Mannix, E.A.; Trochim, W.M.K. The Critical Role of Conflict Resolution in Teams: A Close Look at the Links Between Conflict Type, Conflict Management Strategies, and Team Outcomes. *J. Appl. Psychol.* **2008**, *93*, 170–188. [\[CrossRef\]](#) [\[PubMed\]](#)
11. Abdullah, N.C. Going Green in Urbanisation Area: Environmental Alternative Dispute Resolution as an Option. *Procedia Soc. Behav. Sci.* **2015**, *170*, 401–408. [\[CrossRef\]](#)
12. Zeleznikow, J. Using Artificial Intelligence to Provide Intelligent Dispute Resolution Support. *Group Decis. Negot.* **2021**, *30*, 789–812. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Lydon, D. *Police Legitimacy and the Policing of Protest: Identifying Contextual Influences Associated with the Construction and Shaping of Protester Perceptions of Police Legitimacy and Attitudes to Compliance and Cooperation Beyond the Limits of Procedural Justice and Elaborated Social Identity Approaches*; Canterbury Christ Church University: Canterbury, UK, 2018.
14. Garon, J.M. Reordering the Chaos of the Virtual Arena: Harmonizing Law and Framing Collective Bargaining for Avatar Actors and Digital Athletes. In *Research Handbook on the Law of Virtual and Augmented Reality*; Edward Elgar Publishing: Cheltenham Glos, UK, 2018; pp. 513–566. [\[CrossRef\]](#)
15. Kumar, S. Virtual Venues: Improving Online Dispute Resolution as an Alternative to Cost Intensive Litigation. *J. Marshall J. Comput. Inf. L.* **2009**, *27*, 81.
16. Waihenya, J. The Art & Science of Virtual Proceedings: Shifting The Paradigm in Alternative Dispute Resolution Tribunals. *Altern. Disput. Resol.* **2021**, *1*.
17. Pitt, J.; Ramirez-Cano, D.; Kamara, L.; Neville, B. Alternative Dispute Resolution in Virtual Organizations. In *Engineering Societies in the Agents World VIII*; Springer: Berlin/Heidelberg, Germany, 2008; pp. 72–89. [\[CrossRef\]](#)
18. Lasprogata, G.A. Virtual Arbitration: Contract Law and Alternative Dispute Resolution Meet in Cyberspace. *J. Legal Stud. Educ.* **2001**, *19*, 107. [\[CrossRef\]](#)
19. Viscasillas, P.P. An Arbitrator's Perspective: Online Hearings in Arbitration: The Taking of Evidence. In *Online Dispute Resolution*; Nomos Verlagsgesellschaft mbH & Co. KG: Baden, Germany, 2022; pp. 107–132. [\[CrossRef\]](#)
20. Frolova, E.E.; Rusakova, E.P. Trends in the Development of Alternative Ways of Dispute Resolution of Neo Industrialization Subjects. In *Modern Global Economic System: Evolutional Development vs. Revolutionary Leap*; Popkova, E.G., Sergi, B.S., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 1842–1849.
21. Rohmah, N.Q. Current Issues of The Utilization of Online Dispute Resolution as a Method For International Trade Dispute Settlement. *Ipsa Jure* **2024**, *1*, 25–36. [\[CrossRef\]](#)
22. Ezeldin, A.S.; Abu Helw, A. Proposed Force Majeure Clause for Construction Contracts under Civil and Common Laws. *J. Leg. Aff. Disput. Resolut. Eng. Constr.* **2018**, *10*, 04518005. [\[CrossRef\]](#)
23. Creedon, P.S.; Hayes, A.F. Small Sample Mediation Analysis: How Far Can We Push the Bootstrap. In Proceedings of the Annual Conference of the Association for Psychological Science, New York, NY, USA, 21–24 May 2015.
24. Tofighi, D.; MacKinnon, D.P. Monte Carlo Confidence Intervals for Complex Functions of Indirect Effects. *Struct. Equ. Model.* **2016**, *23*, 194–205. [\[CrossRef\]](#)
25. Hair, J.F.; Sarstedt, M.; Ringle, C.M.; Mena, J.A. An Assessment of the Use of Partial Least Squares Structural Equation Modeling in Marketing Research. *J. Acad. Mark. Sci.* **2012**, *40*, 414–433. [\[CrossRef\]](#)
26. Memon, A.H.; Rahman, I.A. SEM-PLS Analysis of Inhibiting Factors of Cost Performance for Large Construction Projects in Malaysia: Perspective of Clients and Consultants. *Sci. World J.* **2014**, *2014*, 165158. [\[CrossRef\]](#) [\[PubMed\]](#)

27. Hair, J.F.; Ringle, C.M.; Sarstedt, M. Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance. *Long Range Plan.* **2013**, *46*, 1–12. [[CrossRef](#)]
28. Sarstedt, M.; Ringle, C.M.; Hair, J.F. Partial Least Squares Structural Equation Modeling. In *Handbook of Market Research*; Springer: Cham, Switzerland, 2014; pp. 587–632.
29. Civelek, M.E. *Essentials of Structural Equation Modeling*; Zea Books: Lincoln, NE, USA, 2018. [[CrossRef](#)]
30. Avramovic, S.; Alemi, F.; Kanchi, R.; Lopez, P.M.; Hayes, R.B.; Thorpe, L.E.; Schwartz, M.D. US Veterans Administration Diabetes Risk (VADR) National Cohort: Cohort Profile. *BMJ Open* **2020**, *10*, e039489. [[CrossRef](#)] [[PubMed](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

Optimizing food waste anaerobic digestion in Kuwait: Experimental insights and empirical modelling using artificial neural networks

Waste Management & Research

1–12

© The Author(s) 2024

Article reuse guidelines:

sagepub.com/journals-permissions

DOI: 10.1177/0734242X241294247

journals.sagepub.com/home/wmr



Jean H El Achkar¹, Suad Al Radhwan¹, Ahmed M Al-Otaibi²
and Abdul Md Mazid³

Abstract

This study investigates, for the first time, the anaerobic digestion of food waste in Kuwait to optimize methane production through a combination of artificial neural network (ANN) modelling and continuous reactor experiments. The ANN model, utilizing eight hidden neurons and a 70-20-10 split for training, validation and testing sets, yielded mean squared error values of 0.0056, 0.0048 and 0.0059 and coefficient of determination (R^2) values of 0.9942, 0.9986 and 0.9892, respectively. Methane percentages in biogas were predicted using six parameters: biomass type, pH, organic loading rate (OLR), hydraulic retention time (HRT), temperature and reactor volume. To validate the ANN results, continuous reactor experiments were conducted under an OLR of 3 kg VS m⁻³ d⁻¹ and HRT of 20 days at varying temperatures (35°C, 40°C, 45°C, 50°C and 55°C). The experiments demonstrated optimal methane production in the mesophilic range, with ANN predictions closely aligning with experimental data up to 45°C. However, deviations were observed at higher temperatures, particularly under thermophilic conditions beyond 50°C. This study provides novel insights into waste-to-energy initiatives in Kuwait and highlights the potential of integrating computational models with empirical data to enhance biogas production processes.

Keywords

Anaerobic digestion, methane, food waste, continuous reactors, artificial neural network

Received 29th June 2024, accepted 5th October 2024 by Associate Editor Antonis A. Zorpas.

Introduction

With escalating global climate change concerns, many nations are shifting their focus towards reducing greenhouse gas (GHG) emissions by exploring more sustainable and cleaner energy alternatives. Compared to traditional fossil fuels, renewable energy sources offer numerous benefits, including decreased air pollution, environmental sustainability, reduced GHG emissions, and cost-effectiveness (Qi et al., 2022). Among these, biogas has emerged as a prominent solution, derived from the anaerobic degradation of organic waste and is recognized for its environmental advantages (Archana et al., 2024; Garg et al., 2024; Khawer et al., 2022).

The biogas industry has grown considerably, driven by rigorous research and governmental backing. In this context, anaerobic digestion (AD) is regarded as one of the most environmentally friendly alternatives for organic waste management due to its limited environmental footprints (Capson-Tojo et al., 2016; Jin et al., 2021), high potential for energy recovery (Kuruti et al., 2017) and biofertilizers production (Shen et al., 2013). Today, AD is regarded as a low-carbon technology that mitigates carbon emissions and

effectively manages waste (Subbarao et al., 2023). It has been successfully employed to valorize several types of organic waste, including grape pomace, olive pomace, coffee waste, and dairy liquid wastes (El Achkar, 2017, 2022; El Achkar et al., 2018a, 2018c, 2020, 2022, 2023).

In addition to its environmental benefits, biogas production through AD plays a crucial role in the circular economy by transforming waste into valuable resources. The circular economy model emphasizes the continuous use of resources by minimizing waste, maintaining the value of products and materials for as

¹Petroleum Engineering Department, College of Engineering, Australian University, West Mishref, Safat, Kuwait

²Petroleum Research Centre, Kuwait Institute for Scientific Research, Safat, Kuwait

³School of Engineering and Technology, Central Queensland University, Melbourne, VIC, Australia

Corresponding author:

Jean El Achkar, Petroleum Engineering Department, College of Engineering, Australian University, Block 5 – Al Aqsa Mosque Street, West Mishref, Safat 13015, Kuwait.

Email: j.achkar@au.edu.kw

long as possible, and recovering and regenerating products at the end of their service life. AD embodies this principle by converting organic waste into biogas and biofertilizers, which would otherwise contribute to environmental pollution. This not only reduces the burden on landfills but also creates a sustainable cycle of resource utilization (Economou et al., 2024b).

Food waste (FW), in particular, has emerged as a significant global concern. Approximately 1.3 billion tonnes of FW are lost annually, resulting in an estimated economic cost of \$1 trillion. The environmental and social consequences of FW are profound, contributing to 6% of the European Union's GHG (Economou et al., 2024a) and up to 10% of global emissions (Amicarelli et al., 2021) while also exacerbating global food insecurity. AD provides a practical solution to mitigate these emissions by converting FW into energy. Due to its high biodegradable organic content, FW serves as an ideal substrate for biogas production, transforming what is otherwise an environmental liability into a renewable energy source and a valuable agricultural input (Braguglia et al., 2018; Fisgativa et al., 2016). This process aligns with circular economy principles, highlighting the importance of optimizing AD processes for effective FW management.

While countries like Germany, Italy, France, and Australia have made significant progress in incorporating FW into their energy networks, the Gulf region, specifically Kuwait, faces distinct challenges that underline the urgency of tailored solutions. Germany, for instance, boasts 11,084 biogas plants, Italy 1655, and France 837, showcasing the potential of FW in renewable energy endeavours (Suarez et al., 2022). Beyond Europe, Australia's efforts to divert FW from landfills for sustainable energy production are noteworthy. Their initiative to divert 100% of institutional FW could generate 4.86 million m³ of biogas, leading to an annual reduction of up to 508,000 tonnes of GHG emissions (Mahmudul et al., 2022). However, Kuwait's situation contrasts sharply. The country grapples with a significant FW challenge, contributing to environmental and resource management crises (El Bilali and Ben Hassen, 2020). According to the UNEP Food Waste Index Report 2021, Kuwait generates approximately 400,000 tonnes of FW annually, amounting to nearly 95 kg per inhabitant, comparable to other Gulf nations such as the UAE, Oman and Qatar. These figures underscore the pressing need for region-specific research and strategies, especially considering the region's unique climatic, socio-cultural and infrastructural factors.

To address these challenges, innovative approaches are required. Artificial neural networks (ANNs) have emerged as powerful tools for optimizing complex processes such as AD, where they can model the nonlinear relationships between various parameters influencing methane production. Recent studies have demonstrated the superiority of ANN modelling over traditional response surface methods in optimizing biogas and methane production from organic wastes (Parthiban et al., 2023). For instance (Mougari et al., 2021) employed an ANN model to predict biogas and methane yield from various organic wastes, achieving remarkable accuracy with a root mean squared error of 0.9996 and an R^2 of 0.9998. Similarly, Seo et al., 2021 utilized a

recurrent neural network to predict methane gas generation from FW at different organic loading rates (OLRs), identifying optimal methane production rates at specific retention times. Jacob and Banerjee (2016) also harnessed the capabilities of ANNs to optimize the anaerobic co-digestion of diverse organic wastes, yielding commendable prediction accuracy.

Despite these global advancements in biogas production technologies, there is a notable lack of research focused on the AD of FW, specifically in Kuwait, where waste is discharged chiefly in landfills. The region's unique climatic conditions, characterized by high ambient temperatures and arid conditions, pose significant hurdles to traditional AD processes. These challenges can lead to suboptimal methane yields and reduced process stability. Moreover, while ANNs have gained prominence as predictive tools in biogas production (Andrade Cruz et al., 2022; Obileke et al., 2024), there is a scarcity of studies that validate ANN predictions against experimental findings from continuous anaerobic reactors, particularly under extreme climatic conditions. This gap in the literature highlights the need for tailored research that can address the specific challenges faced in regions like Kuwait.

This study aims to bridge these critical gaps by optimizing methane production from FW in Kuwait by integrating ANN modelling with continuous reactor experiments. The key objectives of this research are (1) to assess the performance of the established ANN model in predicting methane yields from FW in Kuwait, (2) to validate these ANN predictions through experimental data obtained from continuous anaerobic reactors and (3) to explore the use of locally acclimatized inoculum in enhancing the efficiency and stability of AD processes in mesophilic and thermophilic temperature ranges.

The ANN model developed in this study is innovative in capturing the complex, nonlinear relationships influencing methane production, offering a crucial tool for optimizing biogas production in regions with challenging environmental conditions such as Kuwait. Additionally, locally acclimatized inoculum, sourced from cow manure in Kuwait, introduces a novel adaptation to the AD process, enhancing efficiency in mesophilic and thermophilic temperature ranges. While prior research has explored various aspects of biogas generation and ANN modelling, there remains a lack of concise comparisons between ANN predictions and experimental findings from continuous anaerobic reactors. Such direct comparisons are critical for assessing the accuracy and reliability of ANN models in real-world scenarios.

By addressing these objectives, this research contributes to optimizing AD processes in Kuwait and aligns with the circular economy principles. The findings from this study are expected to inform industry practices and policy decisions, promoting greater sustainability, energy independence and the responsible management of resources in the region.

Materials and methods

Artificial neural network

Design of the artificial neural network. A single neural network consists of an input layer, one or more hidden layers and an

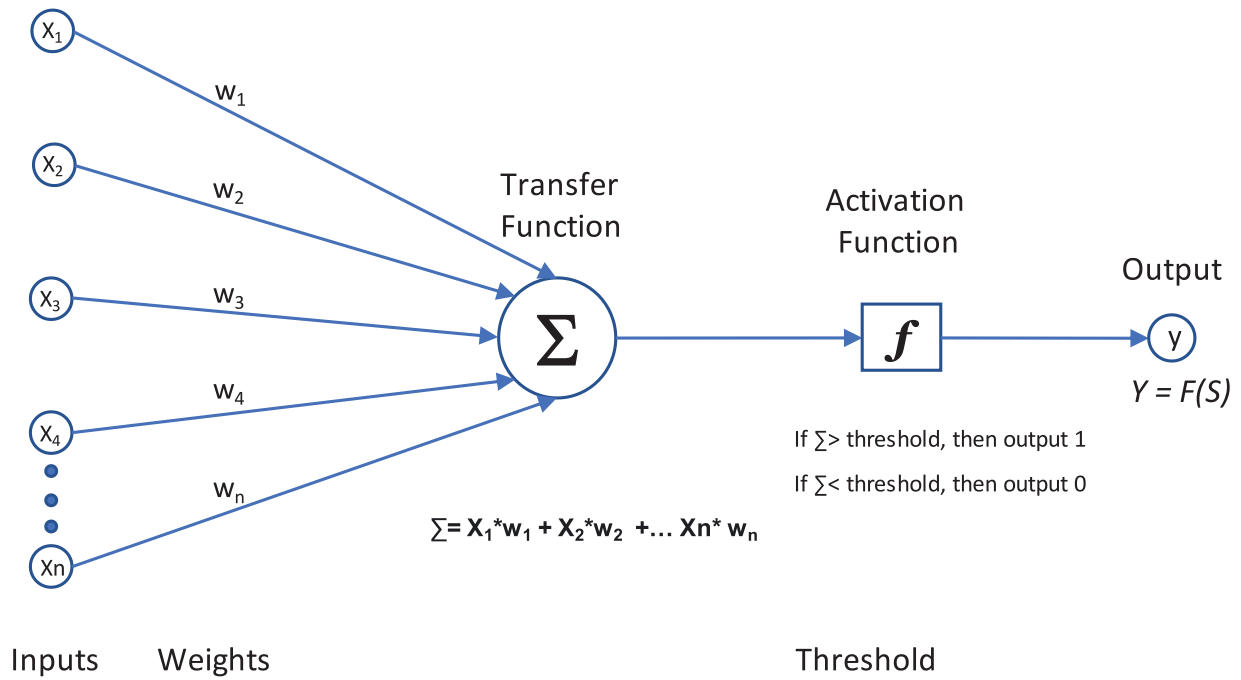


Figure 1. Single neural network model.

output layer (Figure 1). A network's hidden layer neurons establish the complex associations between input and output parameters that result from input and output data.

Each synapse path contains one or more learnable weights ($w_1, w_2, \dots, w_n$) interacting multiplicatively with the input pixels ($x_1, x_2, \dots, x_n$). After that, the neuron receives and sums all synapses currents. If the summed value exceeds a certain threshold, the neuron is fired.

The artificial neuron output can be represented mathematically using equation (1):

$$y = f\left(\sum_{i=0}^i x_i w_i + b\right) \quad (1)$$

where x_i is the i th input, w_i is the weight corresponding to i th input, f is the activation function, and b is bias. Bias represents a constant parameter that is summed before the activation function. The purpose of bias is that it allows the cluster of the classifier to fit the data accurately.

The study used the MATLAB R2021b software combined with the Deep Neural Network Toolbox 14.3 to develop the ANN model. The essential stages involved in this process included:

- **Problem definition:** This primary phase addressed defining the model's objective: to accurately predict methane content resulting from the AD of FW, aiming to minimize the mean square error (MSE).
- **Data preparation:** Ensuring the data's adequacy and relevancy is focal, given that the neural network model's capability and reliability largely depend on it.
- **ANN training:** The Levenberg-Marquardt backpropagation algorithm (Trainlm) was employed in this phase, which is beneficial for its gradient descent technique, optimizing the

sum of square errors by updating network parameters. The Levenberg-Marquardt training algorithm is suitable for training small-sized ANNs.

- **Model validation:** This phase emphasized evaluating the model's performance, with MSE evaluating variance and bias and the R -value determining the correlation between the targets and outputs.

Data collection, preprocessing and segregation. To achieve the ANNs stated objective, data regarding the methane content from AD of FW, accounting for conditions like temperature, OLR and hydraulic retention time (HRT), was imperative. The data underwent preprocessing, which involved normalizing input and output variables to ensure accuracy. This investigation considered data from rigorous research, discarding datasets with inconsistencies arising from variable experimental methodologies.

The neural network parameters chosen as inputs were biomass type, pH, OLR ($\text{kg VS m}^{-3} \text{ d}^{-1}$), HRT (days), temperature ($^{\circ}\text{C}$) and reactor volume (m^3). The desired output was the methane content of biogas. For optimal model training and validation, 140 samples were partitioned into 3 distinct sets: training set (98 samples or 70%), validation set (28 samples or 20%) and testing set (14 samples or 10%).

ANN configuration and training strategy. The neural network's architecture was designed with six input neurons, representing the factors mentioned earlier, and a singular output neuron corresponding to the methane content. During the preliminary assessments, it was observed that the network was prone to overfitting, leading to the integration of the dropout technique. The dropout rate was fine-tuned to 0.5 to balance preventing overfitting and maintaining generalization capability.

The training process involved the feedforward-backpropagation algorithm, streamlining prediction and error correction. The algorithm worked by processing input data, calculating and adjusting weights through layers and iteratively refining predictions based on comparison with actual values. The MATLAB R2021b provided a user-friendly interface, with the Neural Net Time Series option particularly suited for this task. The training utilized the Levenberg-Marquardt algorithm to minimize discrepancies between model outputs and actual values. Post-training, the model underwent testing to assess its predictive capabilities.

Validation of the ANN model. A neural network with eight hidden neurons was crafted for the prediction task. Two critical metrics, the MSE and the determination coefficient (R^2), were employed to ensure reliability. The MSE determines the square difference average between model predictions and targets. Ideally, a minimal MSE value indicates model accuracy. On the other hand, the R^2 value provides insight into the correlation strength between predicted and actual values. An R^2 value nearing 1 signifies a strong correlation.

Lab experimentation and methane assessment

Food waste samples preparation and characterization. In various Kuwaiti households, distinct categories of FW were precisely gathered. Afterward, each kilogram of the sample included 150 g of white rice, 150 g of chicken, 150 g of meat, 150 g of bread, 150 g of mixed vegetables, 150 g of mixed fruits, 50 g of dairy milk and 50 g of biscuits. The selected composition for this study is based on consistent observations from several households, ensuring its relevance to the local context. Following sample preparation, the collected FW samples underwent a thorough processing stage involving fine crushing of the materials. Subsequently, they were carefully stored in glass containers to guarantee their integrity. The containers were stored at a controlled temperature of -20°C within a freezer to preserve the samples under optimal conditions for further analysis and assessment. This systematic approach ensured the reliability and accuracy of the collected data for subsequent research and analysis.

Based on the standard methods outlined by APHA, the FW samples were tested for their total solids (TS) and volatile solids (VS) content (American Public Health Association et al., 2005). A WTW pH metre, model Multi 340i, was used to measure the pH.

Inoculum preparation. The cow manure used as inoculum was collected from a dairy farm in Kuwait during summer. It was passed through a $300\ \mu\text{m}$ sieve to remove large particles and then mixed with water to attain a TS concentration of 5%. Before starting the experiments, the inoculum was subjected to a 14-day deprivation phase to adapt to the experiment temperature and better evaluate the substrate's biodegradability. This was done by storing the inoculum in an anaerobic chamber for 14 days under five different temperatures: 35°C , 40°C , 45°C , 50°C and 55°C ,

without providing any organic material to consume. Once this period was over, the microorganisms were exposed to the substrate to initiate digestion.

Methane production in continuous reactors. The system established for continuous methane production measurement includes three central components. The incubation unit comprised a thermostatic water bath housing four 2 L digesters containing cow manure and FW. Every digester has two sealable tubes, one for extracting the digestate and the other for introducing the input. Each digester was manually agitated for a minute twice daily to ensure optimal mixing (El Achkar, 2017).

For half of the digesters (two out of four), the biogas generated was channelled through a connecting tube from the incubation unit to the CO_2 fixation unit, consisting of a 6 M NaOH solution to capture CO_2 . Consequently, the methane emitted from this setup was recorded in the third unit using a gas meter with a measurement capacity ranging from $1\ \text{mL h}^{-1}$ to $1\ \text{L h}^{-1}$. The remaining two digesters had their biogas directly measured, bypassing the CO_2 fixation stage. To determine the methane percentage, the methane volumes produced by these digesters were contrasted against the biogas volumes.

This experimental setup was subjected to five distinct temperature settings: 35°C , 40°C , 45°C , 50°C and 55°C . The experiments were conducted sequentially, with each temperature condition tested independently in separate runs. After completing the experiment at one temperature, the digesters were thoroughly cleaned and reset before being used for the following temperature. This ensures that each temperature was tested under consistent conditions, making the results representative and directly comparable across the different temperature settings. The uniform FW samples served as the feedstock for all trials. A daily routine of feeding and extraction was followed based on an HRT of 20 days and an OLR set at $3\ \text{kg VS m}^{-3}\ \text{d}^{-1}$. The alkalinity and total volatile acidity (TVA) were also determined per the standardized procedure. All digesters underwent a 60-day operational period, equivalent to thrice the HRT, ensuring that the system reached a stable state, marked by consistent gas production (El Achkar, 2017).

Results and discussion

MATLAB (ANN) predicted methane content

The neural network, which utilized eight hidden neurons, was trained using a data separation strategy of 70%, 20% and 10% for training, validation and testing, respectively. Detailed information about the developed ANN model is found in Table 1, and the model architecture is shown in Figure 2.

Regarding performance metrics, the training set recorded an MSE of 0.0056, while the validation set achieved an MSE of 0.0048, with its best performance observed at 0.0042 during the sixth epoch. The testing set had an MSE of 0.0059. The coefficient of determination (R^2) values were 0.9942, 0.9986 and

Table 1. Detailed information about the developed ANN model.

Parameters	ANN
No. of hidden neurons	8
Training algorithm	Trainlm
No. of training dataset	98
No. of validation dataset	28
No. of testing dataset	14
No. of epochs	8

ANN: artificial neural network.

0.9892 for the training, validation and testing sets, respectively. These metrics indicate that the neural network model is highly effective in predicting methane content from the AD of FW based on the selected parameters. Similarly, Gonçalves Neto et al., 2021 achieved impressive R^2 values up to 0.9929 when modeling biogas production using experimental data from various organic wastes, further validating the reliability of such neural network models in this domain.

During the MATLAB simulation, five OLR values (0.5, 1, 3, 5 and 7 kg VS $\text{m}^{-3} \text{d}^{-1}$) were analyzed at five HRT values (7, 10, 20, 30 and 40 days). Likewise, five different temperatures (35°C, 40°C, 45°C, 50°C and 55°C) were tested, along with three other fixed input variables: biomass type (FW=1), pH=7 and reactor volume of 1 m^3 . Once the ANN model was tested and validated, new input data, which consisted of equation (2), was entered into the MATLAB script.

$$y_{\text{fit}} = \text{nets}(\text{NewInput}) \quad (2)$$

y_{fit} : Predicted methane content based on input parameters.

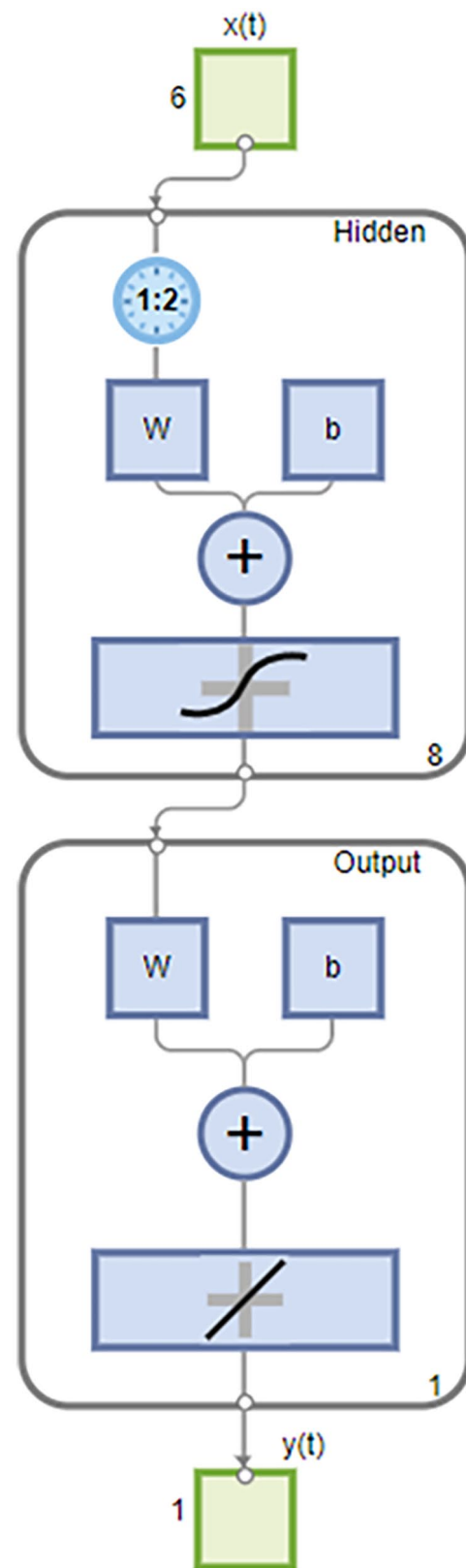
nets : Function representing the trained neural network model, which, when provided with input parameters, returns the corresponding predicted output.

NewInput : Represents the set of input parameters, including variables such as OLR, HRT and temperature, along with fixed parameters like biomass type, pH and reactor volume.

This equation allows MATLAB to process new data through the neural network to estimate methane content based on the input conditions. Table 2 summarizes the predicted methane contents under different OLR, HRT, temperatures, fixed biomass type, pH and reactor volume (testing set).

ANN predicted methane content at different OLRs. Using the MATLAB function, y_{fit} , methane production was estimated at OLRs of 0.5, 1, 3, 5 and 7 kg VS $\text{m}^{-3} \text{d}^{-1}$. As shown in Table 2, simulations were conducted with FW as substrate, set parameters of pH 7, HRT of 20 days, a temperature of 35°C, and reactor volume of 1 m^3 .

At an OLR of 0.5 kg VS $\text{m}^{-3} \text{d}^{-1}$, the model predicted a peak methane content of 70.5%, as shown in Figure 3. Subsequently, a slight decrease to 69.2% was observed at 1 kg VS $\text{m}^{-3} \text{d}^{-1}$. A more

**Figure 2.** ANN model architecture.

ANN: artificial neural network.

pronounced decline became evident as the OLR increased, reaching 63.6% at 7 kg VS $\text{m}^{-3} \text{d}^{-1}$. The methane content's consistent range, between 63% and 71% across the OLRs, attests to the reactor's capacity to sustain high methane outputs, even in

Table 2. ANN predictions for methane content under different OLR, HRT and temperatures.

Biomass type	pH	OLR (kg VS m ⁻³ d ⁻¹)	HRT (days)	T (°C)	Reactor volume (m ³)	Methane content (%)
1. Food waste						
1	7	0.5	20	35	1	70.5
1	7	1	20	35	1	69.2
1	7	3	20	35	1	67.5
1	7	5	20	35	1	65.0
1	7	7	20	35	1	63.6
1	7	3	7	35	1	62.1
1	7	3	10	35	1	64.2
1	7	3	20	35	1	67.5
1	7	3	30	35	1	69.6
1	7	3	40	35	1	72.4
1	7	3	20	40	1	65.0
1	7	3	20	45	1	62.2
1	7	3	20	50	1	52.2
1	7	3	20	55	1	46.6

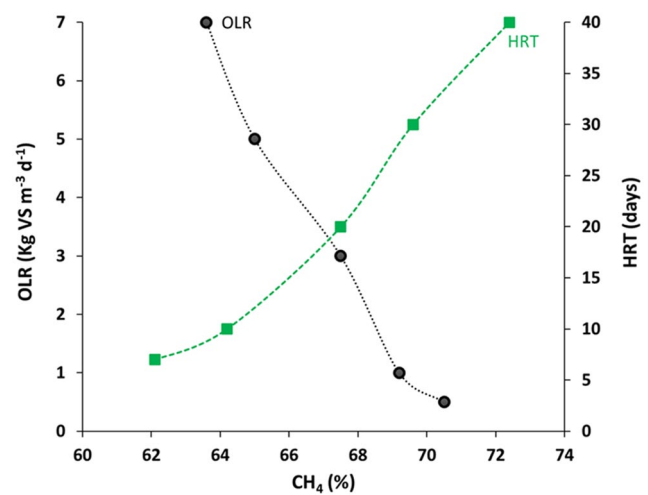
ANN: artificial neural network; OLR: organic loading rate; HRT: hydraulic retention time; VS: volatile solids.

suboptimal conditions. However, literature shows that careful monitoring and regulation of OLR might be necessary to ensure the most efficient operation. Increasing OLRs may accumulate volatile fatty acids (VFAs), disrupting digestion (Jomnonkhaow et al., 2021). A rise in VFA levels can depress the pH, creating an environment that is hostile to methanogens, consequently leading to diminished biogas yields (Al-Sulaimi et al., 2022). Simulation of FW AD using Aspen Plus showed the highest methane content (74.82%–77.10%) with OLRs between 2 and 5 L/day (Anaya Menacho et al., 2022).

ANN predicted methane content at different HRTs. HRT plays a critical role in AD, influencing how long substrates remain in the system and, consequently, the efficiency of microbial activity and methane generation. This section explores its influence based on the ANN model predictions. Using the MATLAB function `yfit`, methane content was forecasted at HRTs of 7, 10, 20, 30 and 40 days, with a consistent OLR of 3 kg VS m⁻³ d⁻¹, a temperature of 35°C and a reactor volume of 1 m³.

The findings from the ANN model shed light on the relationship between HRT and methane yields, echoing some established understandings in the field. As per Figure 3, a peak methane yield of 72.4% at an HRT of 40 days suggests the advantages of allowing substrates more time to break down. In essence, longer HRTs ensure complex organic compounds have ample time for hydrolysis, resulting in more thorough degradation and a higher potential for methane formation.

On the other hand, shorter HRTs might not afford the microbes sufficient time for optimal substrate utilization, possibly leading to the lower methane yield of 62.1% observed at an HRT of 7 days. The upward trend from 7 to 40 days might indicate the increasing efficiency and activity of the methanogenic communities. These bacteria thrive in stable environments, and extended HRTs can offer this stability, minimizing fluctuations in substrate concentration and reducing the risk of washing out essential microbes.

**Figure 3.** ANN methane content predictions at different OLRs and HRTs.

ANN: artificial neural network; OLR: organic loading rate; HRT: hydraulic retention time.

A recent study provided insights, suggesting that longer HRTs foster a favourable environment for methanogenic bacteria, enhancing methane yields (Gaby et al., 2017). This stability supports a balanced internal microbial ecosystem, promoting a cooperative interplay between different bacterial groups, especially acidogens and methanogens.

However, the advantages of longer HRTs are not without potential downsides. Another research paper highlighted the risk of accumulating inhibitory compounds like VFAs and ammoniac nitrogen with extended HRTs (Harun et al., 2019). While VFAs and ammoniac nitrogen are typical intermediate products in digestion, an imbalance can lead to excessive levels. Elevated VFA concentrations can lower digester pH, affecting methanogenic activity, while high ammoniac nitrogen can inhibit these bacteria, reducing methane yields.

Furthermore, while extended HRTs may enhance methane production, they can reduce the processing capacity for a given

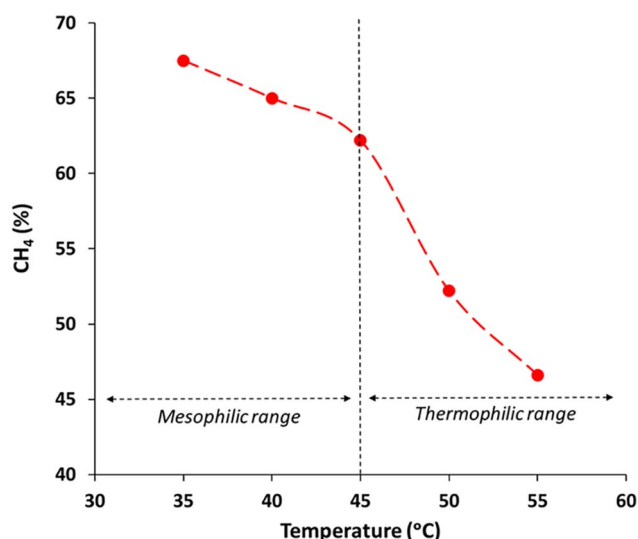


Figure 4. ANN methane content prediction at different temperatures.

ANN: artificial neural network.

digester size. This balance between efficiency and capacity becomes crucial in industrial scenarios where processing large volumes is often a primary concern. Finally, any discussion on HRTs should consider the economic implications. Higher methane yields sound promising, but the costs associated with longer processing times and the potential need for larger reactors must be balanced against these benefits.

ANN predicted methane content at different temperatures. Temperature plays a pivotal role in AD processes, impacting microbial activity and, consequently, methane production. Using the MATLAB function `yfit`, methane content was predicted at different temperatures of 35°C, 40°C, 45°C, 50°C and 55°C, with a maintained pH of 7, OLR of 3 kg VS m⁻³ d⁻¹, HRT of 20 days and reactor volume of 1 m³. As illustrated in Figure 4, the highest predicted methane content from the ANN was 67.5%, achieved at a temperature of 35°C. Moreover, the second highest predicted methane content was 65.0%, obtained at a temperature of 40°C. Conversely, the lowest predicted methane content was 46.6%, achieved at a temperature of 55°C.

In fact, methane production in anaerobic digesters results from complex microbial interactions. The microbial communities responsible for methane production are sensitive to environmental conditions, with temperature being a critical determinant. A recent study found mesophilic anaerobic membrane bioreactors outperform thermophilic ones in co-digesting sewage sludge and FW, offering higher biogas production and better energy recovery. The results suggest mesophilic conditions favour optimizing waste management and bioenergy recovery in smart cities (Cheng et al., 2024). The results predicted by the ANN model were further validated through experiments conducted using continuous reactors under specific conditions. The following section will discuss the detailed findings and implications of these experimental validations.

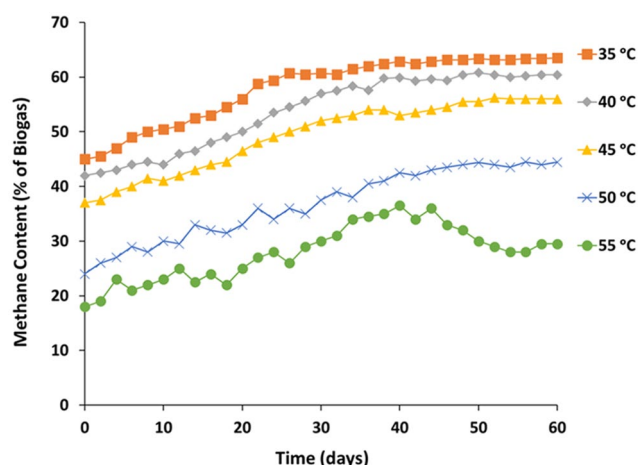


Figure 5. Methane content from continuous reactors under temperatures of 35°C, 40°C, 45°C, 50°C and 55°C.

Methane production validation in continuous reactors

Food waste characteristics and experimental conditions. In this experimental section, all FW samples exhibited TS content of 20% ± 0.5%, with a notable proportion of VS accounting for 78% ± 1.5% of the TS. The pH values recorded for the samples were approximately 7 ± 0.1, without any adjustments to the pH levels. This pH range is consistent with the typical composition of household FW in Kuwait, where the substantial presence of neutral or slightly alkaline components like rice and bread balances the natural acidity of fruits and vegetables. Therefore, the pH value observed in this study accurately reflects the typical pH range for FW in Kuwait, reinforcing the relevance and applicability of the findings to the local context.

Laboratory tests were performed to validate ANN findings and measure the methane content in biogas generated from AD of FW. These tests used continuous reactors and were carried out at five different temperatures: 35°C, 40°C, 45°C, 50°C and 55°C, with an HRT of 20 days and an OLR of 3 kg VS m⁻³ d⁻¹. The HRT and OLR chosen have been demonstrated to be optimum for the AD of comparable substrates (El Achkar et al., 2018b). Given the conditions in Kuwait, especially during the summertime, the locally sourced cow manure used as inoculum originates from an environment where daytime temperatures can reach as high as 55°C. This gives the inoculum a distinct advantage: the manure has adapted to high-temperature conditions. Their prior exposure and acclimatization to extreme heat have prepared microorganisms to handle temperatures ranging from 35°C to 55°C, rendering them suitable for the experiments presented in this section. Using local inoculum from Kuwait for AD under local conditions has not been found previously in the literature.

Methane production trends across temperature ranges. As per Figure 5, and across all temperatures, the methane content generally increases over 60 days. However, there are some differences in how the methane percentages change for each temperature setting.

35°C: Starting at 45%, the methane content at this temperature shows the most consistent and significant increase, reaching 63.5% by day 60. Given that 35°C falls within the mesophilic range, this steady rise is likely due to the ideal conditions for a broad spectrum of methanogens, which tend to thrive in this range. After day 40, the consistent methane content indicates that the system has reached a stable equilibrium where the microbial community efficiently processes the FW into methane.

40°C: The methane content begins at 42% and increases to 60.4% by day 60. While this is also a notable increase, the rise is not as high as observed at 35°C. The temperature is still within the mesophilic range but is nearing its upper boundary, possibly indicating a slightly less optimal environment for some methanogens. The microbial activity might be compromised somewhat, leading to this lesser methane production rate.

45°C: Starting from 39%, the methane content reaches 56% by day 60. As temperatures rise and approach the thermophilic range, the methane production rate decelerates slightly compared to the cooler mesophilic temperatures. Though some thermophilic methanogens thrive at this temperature, the overall community might be experiencing some stress, leading to the observed results.

50°C: Starting at a low of 24%, the methane percentage shows an overall increase but with slight fluctuations, reaching up to 44.5%. Since 50°C is well within the thermophilic range, the microbial community may undergo significant stress, with only specific thermophiles thriving. The fluctuations might indicate periods of adaptation by the microbial community to these elevated temperatures.

55°C: Starting at 18%, the methane content reaches 29.5% by day 60. This range has the lowest methane production of all temperatures. At 55°C, many methanogens, even some thermophiles, might be stressed or inhibited, reducing methane production. However, the nonstop methane production suggests that some specialized thermophiles are still active and contribute to methane generation, albeit at a reduced efficiency. Here, one should highlight a recent study that explored using four thermophilic strains to boost methane production in FW AD. Results demonstrated significant enhancements ranging from 2% to 20% compared to controls. The microbial analysis highlighted the strains' effectiveness in enhancing methane production by reinforcing specific metabolic functions (Wang et al., 2024a).

Analysis of optimal methane production conditions. The results underline the importance of temperature in AD. The mesophilic range (especially around 35°C) appears to offer the most optimal environment for methane production. The transition from mesophilic to thermophilic conditions presents challenges. A recent study demonstrated that AD of potato peel waste at 35°C significantly enhances biogas and methane production, with associated positive shifts in microbial

communities, particularly the dominance of *Methanosarcina*, highlighting the importance of optimizing temperature conditions in AD systems for improved energy yield (Chen et al., 2024). While thermophilic conditions might offer benefits such as faster degradation rates and pathogen reduction, they may not be as efficient in methane production as mesophilic conditions. These reactors have an HRT of 20 days, so the first 20 days are particularly critical. The initial adaptation of the microbial community to the environment is likely completed by then, after which the trends are more reflective of a steady-state operation. The consistent OLR ensures that the observed changes in methane content are predominantly due to temperature effects and not substrate availability.

Role of local inoculum and temperature on methane production. On another note, one of the unique findings of this study is its utilization of the local inoculum acclimated to the harsh environmental conditions prevalent in Kuwait. This inoculum exhibits a distinct resilience, consistently producing methane up to 45°C. Such resilience implies a significant operational advantage for AD processes in Kuwait: the indigenous inoculum can be securely employed to maintain effective digestion as long as the temperatures remain within the 35°C–45°C bracket. This not only streamlines the operational requirements but also emphasizes the potential of harnessing local resources for sustainable solutions, especially given the region's unique climate.

Furthermore, recent studies support the significance of maintaining a temperature of 45°C in AD, as it significantly optimizes methanogenesis, enhances microbial community resilience and improves methane production (Wang et al., 2024b). These findings underscore the viability of 45°C as an alternative to conventional temperatures, particularly in managing temperature fluctuations and optimizing energy efficiency. Integrating this approach with locally adapted inoculum could provide a robust framework for sustainable and efficient AD operations in Kuwait.

Post-experiment analysis: pH, alkalinity and TVA. Evaluating the conditions within the reactors at the end of the experiments is crucial to providing a comprehensive understanding of the observed methane content. For this reason, parameters like pH, alkalinity and TVA were assessed for each temperature setting, as per Table 3.

For the reactors operating at 35°C, the final methane content was measured at 63.5%. The final pH was 7.5, which is a good range for AD. The high alkalinity of 9.2 $\text{geq.CaCO}_3 \text{ L}^{-1}$ provides a strong buffer, ensuring the reactor can handle some acid accumulation without significant pH changes. The TVA was recorded at 0.80 $\text{geq.CH}_3\text{COOH L}^{-1}$, below the 2 $\text{geq.CH}_3\text{COOH L}^{-1}$ limit (Callaghan et al., 2002). The TVA/alkalinity ratio at 0.087 is also below the recommended 0.4, indicating a well-balanced reactor.

At 40°C, the final pH dropped slightly to 7.4. The alkalinity was 8.9 $\text{geq.CaCO}_3 \text{ L}^{-1}$, but the TVA increased to 1.40 $\text{geq.CH}_3\text{COOH L}^{-1}$. This suggests more acid-producing organisms at this temperature. The TVA/alkalinity ratio of 0.157 shows there might be some stress for the methanogens.

Table 3. pH, alkalinity and total volatile acidity at the end of the experiments under different temperatures.

Temperature [°C]	Methane (%)	Final pH	Alkalinity (geq.CaCO ₃ L ⁻¹)	TVA (geqCH ₃ COOH L ⁻¹)	TVA/alkalinity ratio
35	63.5	7.5	9.2	0.80	0.087
40	60.4	7.4	8.9	1.40	0.157
45	56.0	7.2	8.5	1.75	0.206
50	44.5	6.6	7.5	2.85	0.380
55	29.5	6.0	6.5	3.20	0.492

TVA: total volatile acidity.

The reactor at 45°C had a final pH of 7.2. With an alkalinity of 8.5 geq.CaCO₃ L⁻¹ and TVA of 1.75 geqCH₃COOH L⁻¹, this reactor is nearing the upper safety limit. The TVA/alkalinity ratio of 0.206 points to possible challenges at this temperature.

The situation at 50°C is concerning. Methane content decreased significantly to 44.5%, and the pH dropped to 6.6. With alkalinity at 7.5 geq.CaCO₃ L⁻¹ and TVA at 2.85 geqCH₃COOH L⁻¹, the reactor's balance is at risk. The TVA/alkalinity ratio of 0.380 is close to the recommended maximum.

The highest temperature, 55°C, showed the most challenges. The methane content was only 30%, and the pH was very low at 6.0. Alkalinity decreased to 6.5 geq.CaCO₃ L⁻¹ and TVA was high at 3.20 geqCH₃COOH L⁻¹. The TVA/alkalinity ratio of 0.492 is above the recommended level of 0.4, indicating a non-suitable environment for methanogenic bacteria.

In conclusion, as temperature increased from 35°C to 55°C, there was a higher risk of forming inhibitory compounds, such as certain long-chain fatty acids. These compounds can hinder the activity of methanogenic bacteria, subsequently reducing methane yields. This agrees with a recently published paper highlighting that thermophilic anaerobic fermentation produces nearly twice the amount of VFAs compared to mesophilic conditions, demonstrating the influence of temperature on acid production during digestion (Xiong et al., 2024).

Factors influencing methane production. Temperature is a pivotal factor influencing AD, but several other related variables might impact the methane concentration in biogas. The following provides explanations of these factors.

- Thermal stress and microbial inhibition:** Extreme temperatures can induce thermal stress on microbial communities. Prolonged exposure to temperatures nearing the higher end of the thermophilic range (like 55°C) can inhibit or even damage specific microbial populations, particularly more sensitive methanogens. This would directly impact the overall methane yield.
- Protein denaturation and enzymatic deactivation:** Elevated temperatures can cause the denaturation of essential proteins and enzymes within microbial cells. When these enzymes lose their structural integrity, they cannot facilitate the biochemical reactions necessary for breaking organic material into methane.
- Solubility of gases:** The solubility of gases, including methane, decreases as temperature increases. At higher

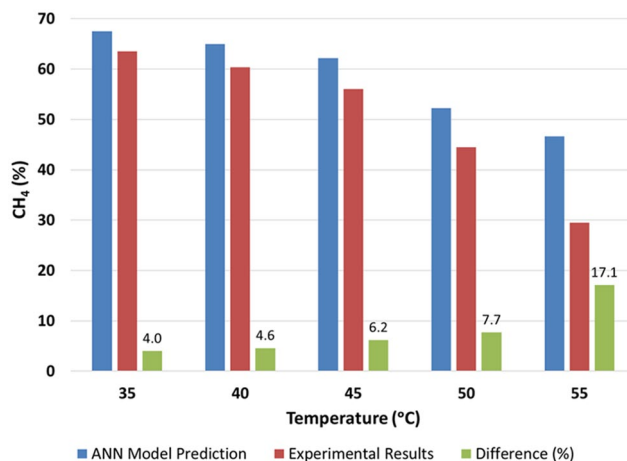


Figure 6. Comparison of methane (%) predictions from the ANN model versus experimental results across different temperatures.

ANN: artificial neural network.

temperatures, more methane might remain dissolved in the liquid phase of the digester, reducing the measured methane percentage in the gaseous phase.

- Faster digestion rates with less efficiency:** While thermophilic conditions can lead to faster digestion rates, they do not necessarily translate to higher efficiency. The rapid breakdown of organic material can sometimes lead to the incomplete degradation of complex compounds, resulting in less methane and more other by-products. A higher proportion of other gases, such as carbon dioxide, hydrogen or unwanted trace gases, dilute the methane concentration.

Comparison between ANN and reactor experiments

Figure 6 outlines a comparative analysis between methane (%) predictions generated by the ANN model and the corresponding experimental results across a range of temperatures. The temperature spectrum examined ranges from 35°C to 55°C, enabling a comprehensive evaluation of the model's predictive efficacy under varying thermal conditions.

Within the dataset, two sets of methane (%) values are juxtaposed: those predicted by the ANN model and those empirically determined through experimentation. A 'Difference %' value accompanies each dataset, quantifying the percentage variance

between the ANN model predictions and the experimental observations. This metric reveals the disparity between the predicted and actual methane (%) values.

In general, one can note that ANN tends to overestimate methane %, as seen in Figure 6. This might stem from several connected reasons. Firstly, the data on which the ANN was trained might have been inclined towards high methane percentages or did not fully capture the complexities of real-world AD processes. Overfitting the ANN is another plausible reason, where the model might have performed exceptionally well on training data but struggled to adapt to new, real-world scenarios.

In real-world setups, numerous factors, such as feedstock type, composition, bacteria, pH, temperature and digester design, play a role in determining methane content. The scenarios from the experimental results may not have been well-represented in the training data for the ANN. Additionally, while ANNs are powerful, they do not inherently understand the underlying chemical or biological processes. This lack of understanding can sometimes make predictions that seem out of place. Furthermore, it is essential to understand that physical and chemical realities, such as kinetic or equilibrium constraints, bind real-world reactor outcomes. These realities can significantly influence results, especially where experimental setups involve specific microbial communities or substrates with distinct characteristics. Lastly, operational conditions, ranging from mixing regimes to potential contaminants, can make a massive difference in biogas production. If these conditions were not accurately mirrored in the ANNs training data, the gap between predictions and experimental results could be widened. Furthermore, the complexity of biogas production is not just a biochemical process; it involves multiple microbial interactions and dependencies, which might not have been represented adequately in the training scenarios provided to the ANN. A recent experimental study emphasizes the importance of understanding microbial dynamics to optimize methane production under different temperature regimes (Wang et al., 2024c).

Upon closer examination of the data, it becomes apparent that, up to a temperature of 45°C, the disparity between the methane (%) values predicted by the ANN model and the experimental measurements remains within an acceptable range. However, beyond this temperature threshold, particularly at 50°C and 55°C, the deviation becomes more pronounced, exceeding what might be acceptable. This observation suggests the model's performance may be satisfactory under mesophilic temperature conditions but may require refinement or calibration to improve accuracy at thermophilic temperatures.

The observed variance underscores the necessity of a rigorous assessment of model performance across diverse operational conditions. Of particular significance is the substantial difference percentage observed at 55°C (17.1%), indicative of a notable deviation with potential implications for practical applications requiring precise methane prediction.

In conclusion, while the ANN model exhibits promise in predicting methane (%) levels across different temperatures, further refinement and validation efforts are imperative to enhance its

accuracy, particularly at higher temperature ranges. Addressing these disparities through recalibration and validation endeavours is essential to ensure the reliability and applicability of the ANN model within academic research and industrial contexts.

Conclusions

This study has demonstrated the significant potential of optimizing AD processes for methane production from FW in Kuwait through the integration of ANN modelling with continuous reactor experiments. The results indicated that methane production peaked at 63.5% at 35°C, gradually declining as temperatures increased, particularly under thermophilic conditions, where methane production at 55°C dropped to 29.5%. Using locally acclimatized inoculum proved advantageous, maintaining efficient digestion and methane production up to 45°C. While the ANN model shows promise in predicting methane (%) levels across various temperatures, further refinement and validation are crucial to improve its accuracy, especially in the higher temperature range from 45°C to 55°C.

Future research should focus on deepening our understanding of the microbial species involved in AD, particularly their composition and interactions under varying environmental conditions. Microbial sequencing technologies are recommended to provide detailed insights into microbial dynamics, which could further optimize methane production and overall process performance.

As the AD field continues to evolve, exploring emerging technologies and innovative approaches is essential. This includes advanced microbial engineering and integrating digital tools such as artificial intelligence and the Internet of Things for real-time monitoring and process optimization. These innovations have the potential to significantly enhance process efficiency and adaptability, particularly in challenging environmental conditions.

The findings from this study, including the successful development of the ANN model, the high experimental methane yields, and the effective use of locally adapted inoculum, contribute to the broader goals of the circular economy and environmental sustainability. This research supports sustainable waste management practices and renewable energy production by optimizing AD processes, offering valuable insights that can inform future studies, industry practices and policy decisions.

In conclusion, the successful optimization of methane production from FW under Kuwait's unique conditions underscores the potential for applying similar approaches in other regions facing environmental challenges. Integrating innovative technologies and a deeper understanding of microbial dynamics will be crucial for advancing the efficiency and broader application of AD systems worldwide.

Acknowledgements

The authors thank the Kuwait Foundation for the Advancement of Sciences (KFAS) for the funding and the Australian University for granting access to their laboratory and facilities for this research.

Declaration of conflicting interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The authors disclosed receipt of the following financial support for the research, authorship and/or publication of this article: The Project was Funded 'Partially' by Kuwait Foundation for the Advancement of Sciences (KFAS) under project code: PP22-15SE-1593.

ORCID iD

Jean H El Achkar  <https://orcid.org/0000-0001-5569-5477>

Data availability statement

Data will be made available after reasonable request.

References

- Al-Sulaimi IN, Nayak JK, Alhimali H, et al. (2022) Effect of volatile fatty acids accumulation on biogas production by sludge-feeding thermophilic anaerobic digester and predicting process parameters. *Fermentation* 8: 184.
- American Public Health Association, Eaton AD, American Water Works Association, et al. (2005) *Standard Methods for the Examination of Water and Wastewater*. Washington, DC: APHA-AWWA-WEF.
- Amicarelli V, Lagioia G and Bux C (2021) Global warming potential of food waste through the life cycle assessment: An analytical review. *Environmental Impact Assessment Review* 91: 106677.
- Anaya Menacho W, Mazid AM and Das N (2022) Modelling and analysis for biogas production process simulation of food waste using Aspen Plus. *Fuel* 309: 122058.
- Andrade Cruz I, Chuenchart W, Long F, et al. (2022) Application of machine learning in anaerobic digestion: Perspectives and challenges. *Bioresource Technology* 345: 126433.
- Archana K, Visckram AS, Senthil Kumar P, et al. (2024) A review on recent technological breakthroughs in anaerobic digestion of organic biowaste for biogas generation: Challenges towards sustainable development goals. *Fuel* 358: 130298.
- Braguglia CM, Gallipoli A, Gianico A, et al. (2018) Anaerobic bioconversion of food waste into energy: A critical review. *Bioresource Technology* 248: 37–56.
- Callaghan FJ, Wase DAJ, Thayanithy K, et al. (2002) Continuous co-digestion of cattle slurry with fruit and vegetable wastes and chicken manure. *Biomass Bioenergy* 22: 71–77.
- Capson-Tojo G, Rouez M, Crest M, et al. (2016) Food waste valorization via anaerobic processes: A review. *Reviews in Environmental Science and Biotechnology* 15: 499–547.
- Chen T, Zhang L, Guo W, et al. (2024) Temperature drives microbial communities in anaerobic digestion during biogas production from food waste. *Environmental Science and Pollution Research* 31: 53823–53838.
- Cheng H, Qin H, Li Y, et al. (2024) Comparative study of high-performance mesophilic and thermophilic anaerobic membrane bioreactors in the co-digestion of sewage sludge and food waste: Methanogenic performance and energy recovery potential. *Science of the Total Environment* 912: 169518.
- Economou F, Chatziparaskeva G, Papamichael I, et al. (2024a) The concept of food waste and food loss prevention and measuring tools. *Waste Management & Research* 42: 651–669.
- Economou F, Voukkali I, Papamichael I, et al. (2024b) Turning food loss and food waste into Watts: A review of food waste as an energy source. *Energies* 17: 3191.
- El Achkar J (2017) *Méthanisation de marc de raisin. Caractérisation et optimisation du procédé et des prétraitements*. These de doctorat, Lorient.
- El Achkar JH (2022) Sustainable solid waste management: Towards a complete and effective strategy. *Arab Journal of STI Policies* 3: 9–17.
- El Achkar JH, Baydoun A, Salameh D, et al. (2018a) Can coffee grounds be considered as a potential for green energy production? In: *2018 4th International Conference on Renewable Energies for Developing Countries (REDEC)*. Presented at the 2018 4th International Conference on Renewable Energies for Developing Countries (REDEC), Beirut, Lebanon, pp.1–6.
- El Achkar JH, El Joahari A, Nassreddine C, et al. (2023) Anaerobic digestion of wastewater sludge for improved energy recovery: Alkaline pre-treatment impact, digestate quality assessment, and reactor design. *Arabian Journal of Science and Engineering* 48: 16109–16121.
- El Achkar JH, Husain AB, Alotaibi N, et al. (2022) Could petroleum sludge be used to produce biomethane as a renewable energy source? In: *Presented at the ADIPEC*. Richardson, TX: OnePetro.
- El Achkar JH, Lendormi T, Salameh D, et al. (2018b) Anaerobic digestion of grape pomace: Effect of the hydraulic retention time on process performance and fibers degradability. *Waste Management* 71: 137–146.
- El Achkar JH, Rohayem C, Salameh D, et al. (2018c) Olive pomace, a source of green energy using anaerobic digestion. In: *2018 4th International Conference on Renewable Energies for Developing Countries (REDEC)*. Presented at the 2018 4th International Conference on Renewable Energies for Developing Countries (REDEC), Beirut, Lebanon, pp.1–6.
- El Achkar JH, Ziade R, Louka N, et al. (2020) Treatment of dairy waste by anaerobic digestion to produce methane as green energy. In: *2020 5th International Conference on Renewable Energies for Developing Countries (REDEC)*. Presented at the 2020 5th International Conference on Renewable Energies for Developing Countries (REDEC), Marrakech, Morocco, pp.1–6.
- El Bilali H and Ben Hassen T (2020) Food waste in the countries of the Gulf Cooperation Council: A systematic review. *Foods* 9: 463.
- Fisgativa H, Tremier A and Dabert P (2016) Characterizing the variability of food waste quality: A need for efficient valorisation through anaerobic digestion. *Waste Management* 50: 264–274.
- Gaby JC, Zamanzadeh M and Horn SJ (2017) The effect of temperature and retention time on methane production and microbial community composition in staged anaerobic digesters fed with food waste. *Biotechnology for Biofuels* 10: 302.
- Garg A, Basu S, Shetti NP, et al. (2024) Biowaste to bioenergy nexus: Fostering sustainability and circular economy. *Environmental Research* 250: 118503.
- Gonçalves Neto J, Vidal Ozorio L, Campos de Abreu TC, et al. (2021) Modeling of biogas production from food, fruits and vegetables wastes using artificial neural network (ANN). *Fuel* 285: 119081.
- Harun N, Hassan Z, Zainol N, et al. (2019) Anaerobic digestion process of food waste for biogas production: A simulation approach. *Chemical Engineering & Technology* 42: 1834–1839.
- Jacob S and Banerjee R (2016) Modeling and optimization of anaerobic codigestion of potato waste and aquatic weed by response surface methodology and artificial neural network coupled genetic algorithm. *Bioresource Technology* 214: 386–395.
- Jin C, Sun S, Yang D, et al. (2021) Anaerobic digestion: An alternative resource treatment option for food waste in China. *Science of the Total Environment* 779: 146397.
- Jomnonkhaow U, Uwineza C, Mahboubi A, et al. (2021) Membrane bioreactor-assisted volatile fatty acids production and *in situ* recovery from cow manure. *Bioresource Technology* 321: 124456.
- Khawer MUB, Naqvi SR, Ali I, et al. (2022) Anaerobic digestion of sewage sludge for biogas & biohydrogen production: State-of-the-art trends and prospects. *Fuel* 329: 125416.
- Kuruti K, Begum S, Ahuja S, et al. (2017) Exploitation of rapid acidification phenomena of food waste in reducing the hydraulic retention time (HRT) of high rate anaerobic digester without conceding on biogas yield. *Bioresource Technology* 226: 65–72.
- Mahmulul HM, Akbar D, Rasul MG, et al. (2022) Estimation of the sustainable production of gaseous biofuels, generation of electricity, and reduction of greenhouse gas emissions using food waste in anaerobic digesters. *Fuel* 310: 122346.
- Mougari NE, Largeau JF, Himrane N, et al. (2021) Application of artificial neural network and kinetic modeling for the prediction of biogas and methane production in anaerobic digestion of several organic wastes. *International Journal of Green Energy* 18: 1584–1596.
- Obileke K, Makaka G, Tangwe S, et al. (2024) Improvement of biogas yields in an anaerobic digestion process via optimization technique.

- Environment, Development and Sustainability*. Epub ahead of print 7 February 2024. DOI: 10.1007/s10668-024-04540-6.
- Parthiban A, Sathish S, Suthan R, et al. (2023) Modelling and optimization of thermophilic anaerobic digestion using biowaste. *Environmental Research* 220: 115075.
- Qi M, Liu Y, He T, et al. (2022) System perspective on cleaner technologies for renewable methane production and utilisation towards carbon neutrality: Principles, techno-economics, and carbon footprints. *Fuel* 327: 125130.
- Seo KW, Seo J, Kim K, et al. (2021) Prediction of biogas production rate from dry anaerobic digestion of food waste: Process-based approach vs. recurrent neural network black-box model. *Bioresource Technology* 341: 125829.
- Shen F, Yuan H, Pang Y, et al. (2013) Performances of anaerobic co-digestion of fruit & vegetable waste (FVW) and food waste (FW): Single-phase vs. two-phase. *Bioresource Technology* 144: 80–85.
- Suarez E, Tobajas M, Mohedano AF, et al. (2022) Energy recovery from food waste and garden and park waste: Anaerobic co-digestion versus hydrothermal treatment and anaerobic co-digestion. *Chemosphere* 297: 134223.
- Subbarao PMV, D'Silva TC, Adlak K, et al. (2023) Anaerobic digestion as a sustainable technology for efficiently utilizing biomass in the context of carbon neutrality and circular economy. *Environmental Research* 234: 116286.
- Wang N, Xiao M, Zhang S, et al. (2024a) Evaluating the potential of different bioaugmented strains to enhance methane production during thermophilic anaerobic digestion of food waste. *Environmental Research* 245: 118031.
- Wang Z, He H, Yan J, et al. (2024b) Influence of temperature fluctuations on anaerobic digestion: Optimum performance is achieved at 45°C. *Chemical Engineering Journal* 492: 152331.
- Wang Z, Li H, Wang P, et al. (2024c) Comparison of anaerobic co-digestion of vacuum toilet blackwater and kitchen waste under mesophilic and thermophilic conditions: Reactor performance, microbial response and metabolic pathway. *Journal of Environmental Management* 366: 121725.
- Xiong H, Liu L, Song B, et al. (2024) Mesophilic and thermophilic fermentation of activated sludge for volatile fatty acids production: focusing on anaerobic degradation of carbohydrate and protein. *Environmental Technology*. Epub ahead of print 29 January 2024. DOI: 10.1080/09593330.2024.2306152.

Article

Variations and Trends in 115 Years of Graded Daily Precipitation Records at Three Hydrometeorological Stations in Finland

Masoud Irannezhad ^{1,2,*} , Zahrah Abdulghafour ¹, Retaj AlQallaf ¹, Fadak Abdulreda ¹, Ghadeer Shamsah ¹ and Hajar Alshammari ¹

¹ Department of Civil Engineering, College of Engineering, Australian University, West Mishref, Safat 13015, Kuwait; zahrah.abdulghafour@gmail.com (Z.A.); ritajalqallaf@outlook.com (R.A.); fadak17@outlook.com (F.A.); gs22x.s@gmail.com (G.S.); alshmmeryhajar@gmail.com (H.A.)

² Water, Energy and Environmental Engineering Research Unit, Faculty of Technology, University of Oulu, 90014 Oulu, Finland

* Correspondence: m.irannezhad@au.edu.kw; Tel.: +965-66102526

Abstract: This study investigated the variability and trends in 115 years (1909–2023) of daily precipitation observed at three hydrometeorological stations in southern (Kaisaniemi), central (Kajaani), and northern (Sodankylä) Finland. We also identified the most significant climate teleconnections influencing daily precipitation variability at these three stations during the period 1951–2023. The daily precipitation records were primarily classified into six grades, including very light (≤ 1 mm), light ($1 < \leq 5$ mm), moderate ($5 < \leq 10$ mm), heavy ($10 < \leq 15$ mm), very heavy ($15 < \leq 20$ mm), and extreme (> 20 mm). On average, the most intense daily precipitation was determined at the Kaisaniemi station in southern Finland. At this station, however, very light and light precipitation showed the lowest frequency, but other graded daily precipitation events were the most frequent. At all three stations, the intensity of very light precipitation significantly declined during the past 115 years, while its frequency increased. The highest rates of such decreases and increases in the intensity and frequency of very light daily precipitation were found at the Sodankylä stations in northern Finland, respectively, but the lowest rates were at the Kaisaniemi station in the south. At the Kajaani station in central Finland, the intensity of light precipitation decreased, but very heavy precipitation intensified. At this station, however, the number of both moderate and heavy precipitation events increased over time. Finally, historical variations in both the intensity and frequency of graded daily precipitation events in Finland showed significant relationships with different climate teleconnections, particularly the Scandinavia (SCAND) and the North Atlantic Oscillation (NAO) patterns.

Keywords: frequency; intensity; precipitation; teleconnections; trend; water resources



Citation: Irannezhad, M.; Abdulghafour, Z.; AlQallaf, R.; Abdulreda, F.; Shamsah, G.; Alshammari, H. Variations and Trends in 115 Years of Graded Daily Precipitation Records at Three Hydrometeorological Stations in Finland. *Water* **2024**, *16*, 2684. <https://doi.org/10.3390/w16182684>

Academic Editor: Paul Kucera

Received: 23 August 2024

Revised: 17 September 2024

Accepted: 18 September 2024

Published: 20 September 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Global mean surface air temperature (SAT) warmed by 1.09 °C in 2011–2020, compared to the period 1850–1900, particularly in response to the significant increases in the anthropogenic concentrations of greenhouse gas (GHG) emissions to the Earth's atmosphere [1]. Sea surface temperature (SST) also increased worldwide, mainly due to the significantly higher atmospheric CO₂ concentration in recent decades [2]. Based on the Clausius–Clapeyron (C–C) relationship, such warmer SAT and SST fundamentally increase atmospheric moisture content [3], thereby particularly leading to significant changes in different characteristics (mainly in terms of intensity and frequency) of extreme precipitation events (EPEs) around the world [4–6]. Such alterations in EPEs have already posed serious economic, social, and environmental sustainability challenges to humanity, particularly in developing countries with high population density, vulnerable infrastructures, and poor land-use management [7].

Globally, the intensity and frequency of EPEs have substantially increased in recent decades [1]. However, these increases are not essentially translated to similar alterations in

such characteristics of EPEs on regional and local scales [8]. To investigate historical and future changes in EPEs around the world, most of the previous studies [9–11] applied a set of extreme precipitation indices recommended by the Expert Team on Climate Change Detection and Indices (ETCCDI) [12]. These extreme indices were principally developed based on daily precipitation amounts less, equal to, or greater than a couple of predefined absolute values, threshold numbers, or long-term NN^{th} percentiles (e.g., $NN = 99$) [13]. There are also several studies [14–16] focusing on extreme value analysis (EVA) approaches, like the peak-over-threshold (POT), for evaluating spatio-temporal variability and changes in regional and local EPEs. A few other studies, however, defined the characteristics of EPEs based on different grades of daily precipitation amounts [17–19]. Although we have already applied extreme precipitation indices [20] and the POT approach [21] for investigating spatio-temporal changes in EPEs in Finland, there is still a lack of studies on variations and trends in graded daily precipitation records throughout this country.

In the era of global warming, it is not only important to investigate regional precipitation changes but also to explain their different underlying physical mechanisms. In hydrology, the spatio-temporal variability across a region is generally related to the atmospheric water content sources and transport paths [22] naturally controlled by different large-scale patterns in atmospheric circulation around the Earth [23–25]. In general, these patterns refer to stable, repeating, and extensive modes of atmospheric pressure anomalies exposing the predominant airflow across a widespread geographical area [26]. They also describe the persistent variability in the natural incidence of chaotic actions in the global climate system [27]. The strength and effects of such patterns across a region through a certain period of the year are principally quantified by numerical indices called “climate teleconnections” [27]. The primary components of such climate teleconnections and their effects on historical variability in regional EPEs around the world have been previously reviewed [6,28–32]. For Finland, we already reported influential climate teleconnections for variability in EPEs identified by applying the extreme precipitation indices [20] and the POT approach [21]. However, understanding and explaining the role of climate teleconnections in the spatio-temporal variability and trends in historically graded daily precipitation records throughout Finland is still well motivated.

This study aimed to investigate long-term historical graded daily precipitation events throughout Finland and their relationships with the well-known large-scale climate teleconnections. Accordingly, the specific objectives were to: (1) summarize statistical analyses of 115-year (1909–2023) graded daily precipitation records at three hydrometeorological stations in northern, central, and southern Finland; (2) determine significant trends in both the intensity and frequency of such historical graded daily precipitation records; and (3) identify influential climate teleconnections strongly influencing such variabilities and trends in historical graded daily precipitation events throughout the country. Based on [33], such observational studies can improve our knowledge about the effects of global warming on climatic conditions and, consequently, water resources availability in cold regions, playing an important role in acting towards achieving the 2030 United Nations Sustainable Development Goals (SDGs) adopted in 2015 [34].

2. Materials and Methods

2.1. Study Area and Data Used

Finland is located in the boreal environment [35] of northern Europe (Figure 1a). Its climate is substantially affected by the latitudinal gradient, the Baltic Sea, the Scandinavian mountains, the Atlantic Ocean, and continental Eurasia [36]. Based on the Köppen–Geiger climate classification system, Finland generally experiences no dry season [37]. In this country, summers are warm and mild (Dfb) in southwestern coastal areas while cold and short (Dfc) in most other parts [37]. However, a strong latitudinal gradient significantly controls SAT variability in Finland. Accordingly, both annual mean SAT [38] and precipitation [39] naturally increase in the south to north direction throughout this country (Figure 1b,c).

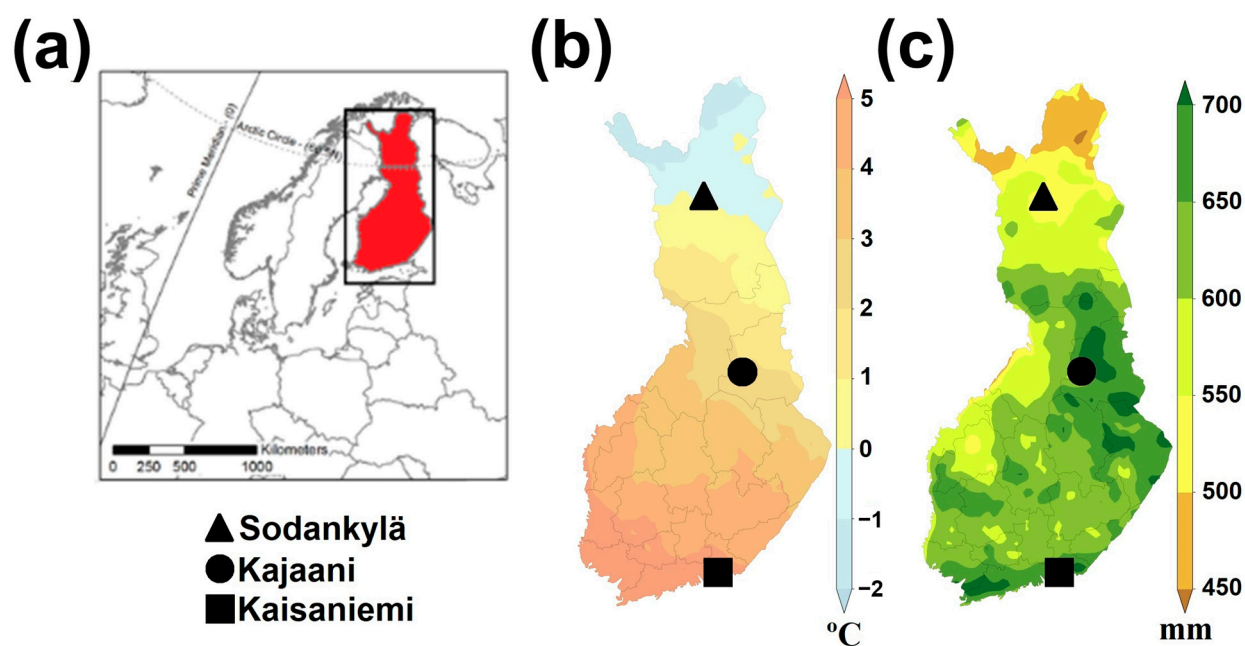


Figure 1. Map of (a) northern Europe with Finland colored red; (b) average of annual mean SAT (°C) and (c) average of annual precipitation (mm) throughout Finland during the latest normal climate period (1991–2020). Assembled based on [40].

For this study, three hydrometeorological stations of Kaisaniemi, Kajaani, and Sodankylä in southern, central, and northern Finland, respectively, were selected (Figure 1). These stations (i) have 115 years of daily precipitation records from 1909 to 2023; (ii) represent all three southern, central, and northern latitudes of Finland; and (iii) show the spatial pattern of precipitation distribution throughout the country. In our previous studies [41–43], we comprehensively explained the geographical coordinates, climatic conditions, devices, and techniques for measuring precipitation at all three Kaisaniemi, Kajaani, and Sodankylä stations. During the 115 years, a few hundred meters of dislocation of the stations, a minor missing data percentage, and a small difference in summertime precipitation due to applying different measuring devices and techniques were almost inevitable [44]; however, it might not practically influence long-term precipitation variability and trend analyses [42].

According to our current knowledge about the large-scale atmospheric circulation patterns influencing SAT and precipitation patterns in Finland [38,39,45,46], this study selected six climate teleconnections (Nos. 1–6 in Table 1). The main features and mechanisms of such teleconnections, as well as their natural influences on climate variability across northern Europe, are completely explained by [27]. Based on the 1981–2010 climatology, the standardized monthly time series (since January 1950) of these six climate teleconnections were obtained from the Climate Prediction Center (CPC) at the National Oceanic and Atmospheric Administration (NOAA), USA, freely available at <https://www.cpc.ncep.noaa.gov/data/teledoc/telecontents.shtml> (accessed on 10 January 2024). For this study, the average values of these monthly time series from January to December during a year were calculated as annual climate teleconnections for the years 1950–2023. Using the standardized monthly time series, seasonal climate teleconnections for winter (December–February), spring (March–May), summer (June–August), and autumn (September–November) for the years 1951–2023 were also calculated. Accordingly, for example, winter 1951 (2023) referred to the period between 1 December 1950 (2022) and the end of February 1951 (2023).

Table 1. Summary of climate teleconnections considered for this study.

No.	ID	Climate Teleconnection	Source	References
1	AO	Arctic Oscillation	CPC	[47]
2	EA	East Atlantic	CPC	[48]
3	EA/WR	East Atlantic/West Russia	CPC	[48,49]
4	NAO	North Atlantic Oscillation	CPC	[48]
5	POL	Polar/Eurasia pattern	CPC	[48]
6	SCAND	Scandinavia pattern	CPC	[48,50]

2.2. Intensity and Frequency Indices

A number of intensity and frequency indices were defined to analyze historical daily precipitation characteristics in Finland based on 1, 5, 10, 15, and 20 mm boundaries [17], grouped into two categories: long-term (Table 2) and annual (Table 3). The long-term intensity indices were used to investigate statistical characteristics of graded daily precipitation records during the full 115 years of our study period (1909–2023). However, the annual indices were employed for determining statistically significant trends in interannual fluctuations of graded daily precipitation intensity and frequency during the period 1909–2023. Similarly, the long-term frequency indices were also described by their interannual variations.

Table 2. Long-term intensity and frequency indices used to analyze historical daily precipitation in Finland based on 1, 5, 10, 15, and 20 mm boundaries.

Characteristic	ID	Description	Units
Intensity	iVLPt	0 mm < Daily precipitation $\leq$ 1 mm	mm day ^{−1}
	iLPt	1 mm < Daily precipitation $\leq$ 5 mm	
	iMPt	5 mm < Daily precipitation $\leq$ 10 mm	
	iHPt	10 mm < Daily precipitation $\leq$ 15 mm	
	iVHPt	15 mm < Daily precipitation $\leq$ 20 mm	
	iEPt	Daily precipitation $\geq$ 20 mm	
Frequency	fVLPt	0 mm < Number of daily precipitation events $\leq$ 1 mm	days year ^{−1}
	fLPt	1 mm < Number of daily precipitation events $\leq$ 5 mm	
	fMPt	5 mm < Number of daily precipitation events $\leq$ 10 mm	
	fHPt	10 mm < Number of daily precipitation events $\leq$ 15 mm	
	fVHPt	15 mm < Number of daily precipitation events $\leq$ 20 mm	
	fEPt	Number of daily precipitation events $\geq$ 20 mm	

Note: i: intensity; V: very; L: light; M: moderate; H: heavy; E: extreme; Pt: daily precipitation; and f: frequency.

2.3. Statistical Analyses

The Mann-Kendall non-parametric test was [51,52] applied for detecting statistically significant ($p < 0.05$) trends in annual intensity and frequency indices at all stations studied during the period 1909–2023. However, the trend-free pre-whitening (TFPW) method [53] was used to determine statistically significant ($p < 0.05$) trends in time series for annual intensity and frequency indices with positive autocorrelation. To calculate the magnitude of such significant trends, the Sen's slope method [54] was employed. The slope of trends in annual intensity and frequency indices were normalized by their long-term (1909–2023) median values, expressed as a percentage. The Spearman's rank correlation (ρ) [55] was used to measure relationships of annual intensity and frequency indices with different climate teleconnections during the period 1951–2023. In the existence of autocorrelation in the time series studied, the residual bootstrap (RB) method [56] with 5000 independent replications was applied for estimating the standard deviations of the $|\rho$ -values. Such statistical approaches have commonly been used in previous studies investigating climate change and its impacts on hydrology and water resources around the world [57–61].

Table 3. Annual intensity and frequency indices used to analyze historical daily precipitation in Finland based on 1, 5, 10, 15, and 20 mm boundaries.

Characteristic	ID	Description	Units
Intensity	iAAVLPT	Ratio of annual total precipitation for (0 mm < daily precipitation $\leq$ 1 mm) to number of occurrences for each year	mm day ^{−1} year ^{−1}
	iAALPt	Ratio of annual total precipitation for (1 mm < daily precipitation $\leq$ 5 mm) to number of occurrences for each year	
	iAAMPt	Ratio of annual total precipitation for (5 mm < daily precipitation $\leq$ 10 mm) to number of occurrences for each year	
	iAAHPt	Ratio of annual total precipitation for (10 mm < daily precipitation $\leq$ 15 mm) to number of occurrences for each year	
	iAAVHPt	Ratio of annual total precipitation for (15 mm < daily precipitation $\leq$ 20 mm) to number of occurrences for each year	
	iAAEPt	Ratio of annual total precipitation for (daily precipitation $\geq$ 20 mm) to number of occurrences for each year	
Frequency	fACVLPet	Number of events (0 mm < daily precipitation $\leq$ 1 mm) for each year	days year ^{−1}
	fACLPEt	Number of events (1 mm < daily precipitation $\leq$ 5 mm) for each year	
	fACMPet	Number of events (5 mm < daily precipitation $\leq$ 10 mm) for each year	
	fACHPEt	Number of events (10 mm < daily precipitation $\leq$ 15 mm) for each year	
	fACVHPEt	Number of events (15 mm < daily precipitation $\leq$ 20 mm) for each year	
	fACEPet	Number of days with precipitation $\geq$ 20 mm	

Note: i: intensity; AA: average annual; V: very; L: light; M: moderate; H: heavy; E: extreme; Pt: daily precipitation; P: Precipitation; f: frequency; AC: annual count; and Et: events.

3. Results

On average, the amount of very light daily precipitation (iVLPt) in Finland during the period 1909–2023 ranged from 0.31 to 0.44 mm (Figure 2a). Such graded daily precipitation events were mostly measured in 53–130 days of a year (Figure 2e). Interestingly, the Sodankylä station experienced the lowest intensity (Figure 2a) but the highest frequency (Figure 2e) of very light daily precipitation events. The light daily precipitation (iLPt) was between 2.35 and 2.73 mm (Figure 2b), observed in 55–93 days per year (Figure 2f). The most intense (iLPt) (Figure 2b) and frequent (fLPt) (Figure 2f) light daily precipitation events were usually experienced at the Kajaani station in central Finland. The highest intensities (iMPt, iHPt, iVHPt, and iEPt) and frequencies (fMPt, fHPt, fVHPt, and fEPt) of daily precipitation greater than 5 mm were generally recorded at the Kaisaniemi station in southern Finland (Figure 2b–d,f–h). The range of moderate daily precipitation intensity (iMPt) was from 6.70 to 7.30 mm (Figure 2b), occurring 32–37 times per year (Figure 2f). In Finland, both the intensities (Figure 2c,d) and frequencies (Figure 2g,h) of all heavy, very heavy, and extreme daily precipitation events increased from the north (Sodankylä) to south (Kaisaniemi) direction. The only exception referred to the lower frequency of extreme daily precipitation (fEPt) in central (Kajaani) rather than in northern (Sodankylä) Finland (Figure 2h). The intensity of extreme daily precipitation events (Figure 2d) ranged between 22.10 and 33.34 mm, experienced only 1–8 times in each year (Figure 2h).

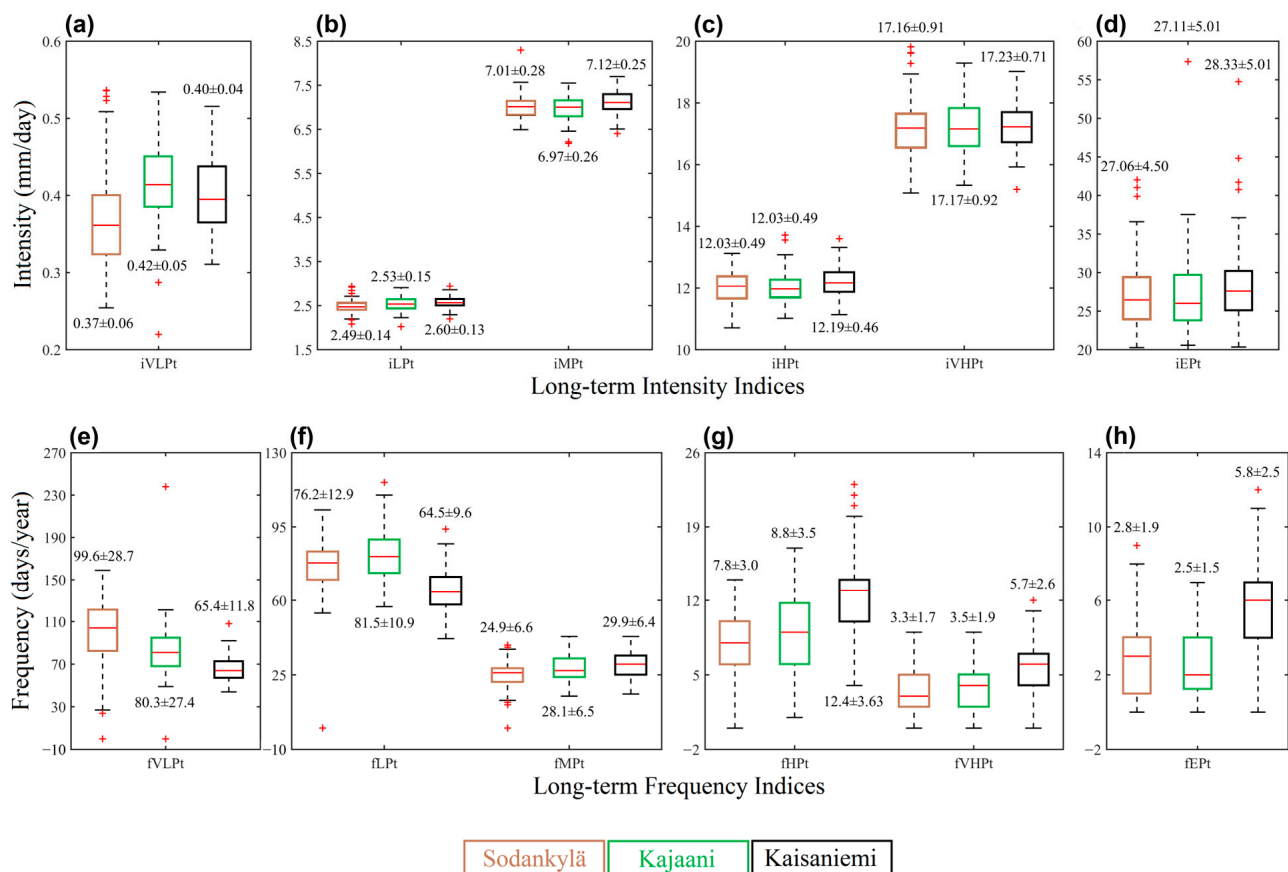


Figure 2. Box-and-whisker plots of long-term (1909–2023) daily precipitation (a–d) intensity and (e–h) frequency indices (Table 2) at the Sodankylä, Kajaani, and Kaisaniemi stations in northern, central, and southern Finland, respectively. Mean value (μ) $\pm$ standard deviation (σ) as statistical parameters are given on top of each index. The outliers are represented by red “+” symbols.

The annual average intensity of very light daily precipitation events (iAAVLPEt) showed statistically significant ($p < 0.05$) decreasing trends, ranging from 0.36 to 0.42%, at all three stations studied during the period 1909–2023 (Figure 3a). However, the annual frequency of such events (iACVLPet) substantially increased by 64% at Sodankylä, 81% at Kajaani, and 104% at Kaisaniemi (Figure 3b). At Kajaani in central Finland, the annual intensity of light daily precipitation (iAALPEt) decreased by 2.54%, while there was an increasing trend (by 17.16%) in the annual intensity of very high daily precipitation time series (Figure 3a). At this station (Kajaani), significant trends were found in the annual frequencies of both moderate (fACMPet) and high (fACHPEt) daily precipitation events at the rates of 27% and 9%, respectively (Figure 3b). The Kaisaniemi station experienced substantial decreasing trends in the annual intensity of moderate daily precipitation (iAAMPet) and the annual frequency of extreme precipitation events (fACEPEt) during the 100-years study period (Figure 3b). At Sodankylä in northern Finland, no significant trends were found in annual intensity and frequency indices other than iAAVLPEt and FACVLPet (Figure 3).

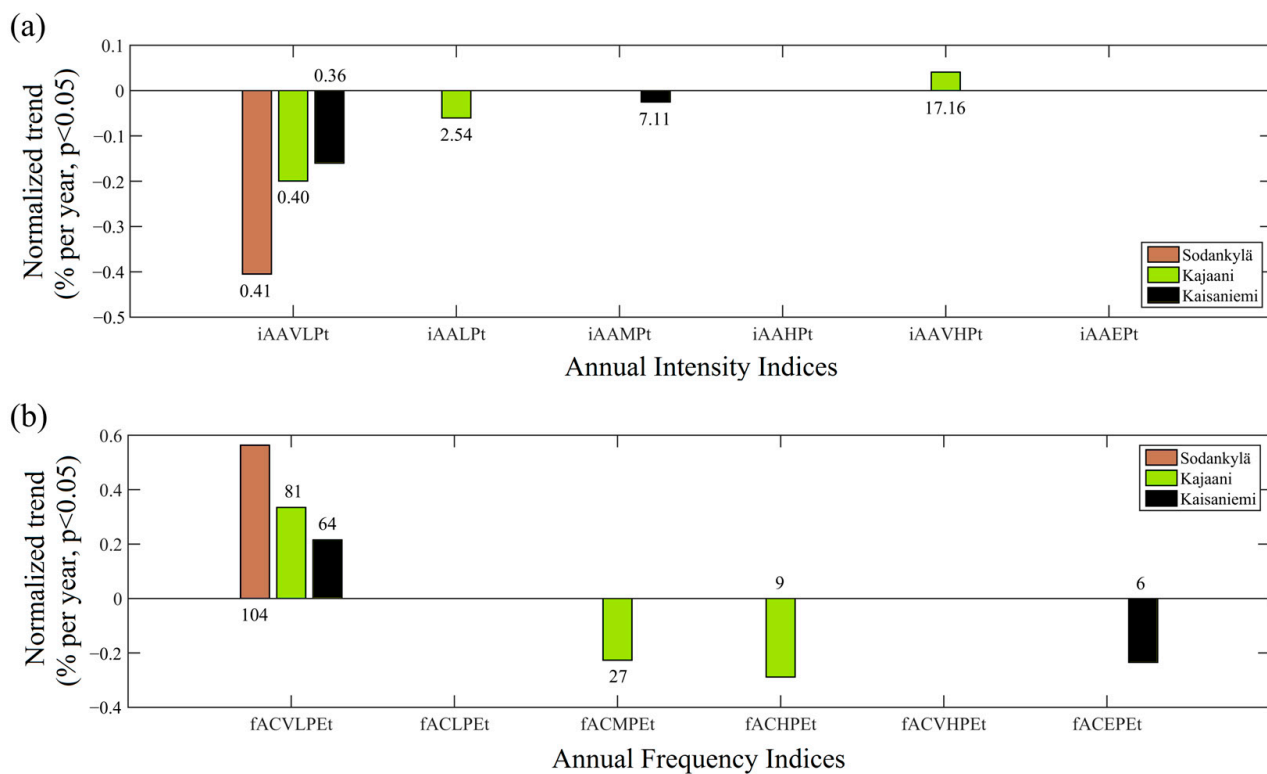
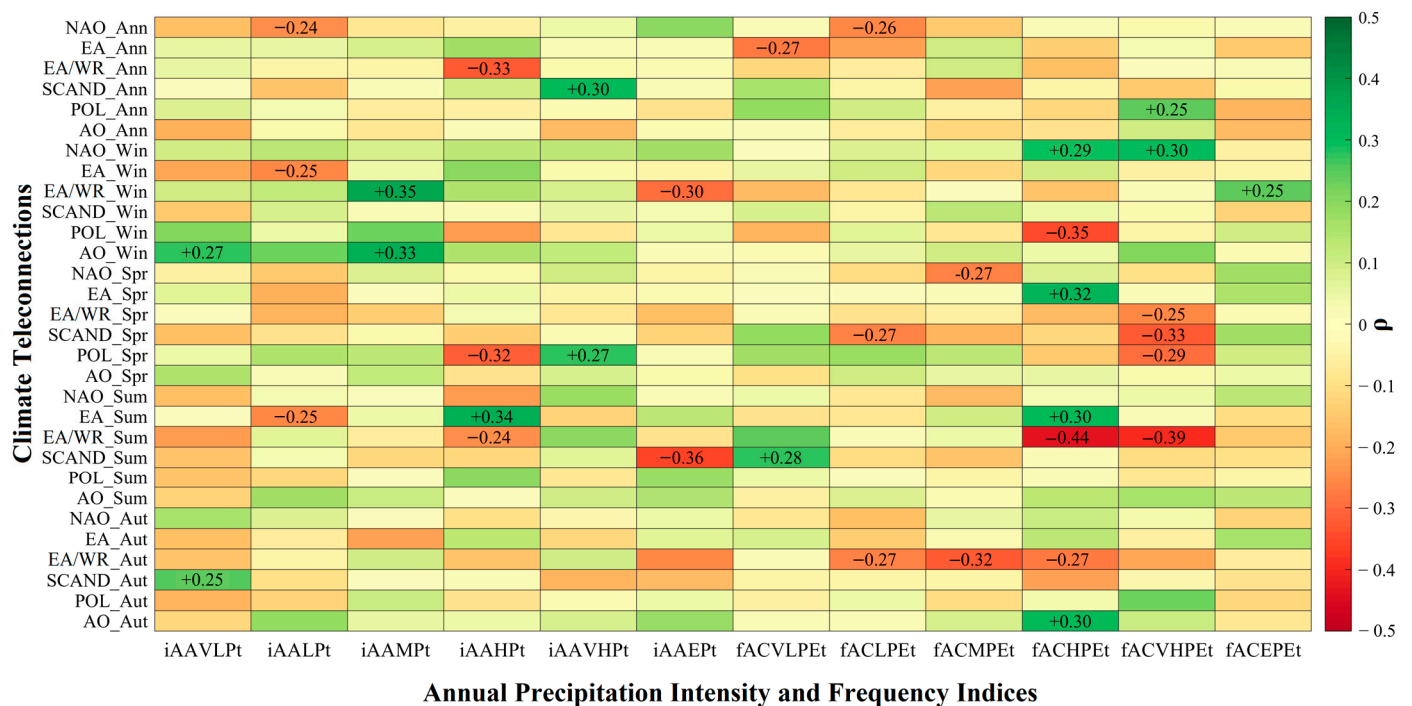
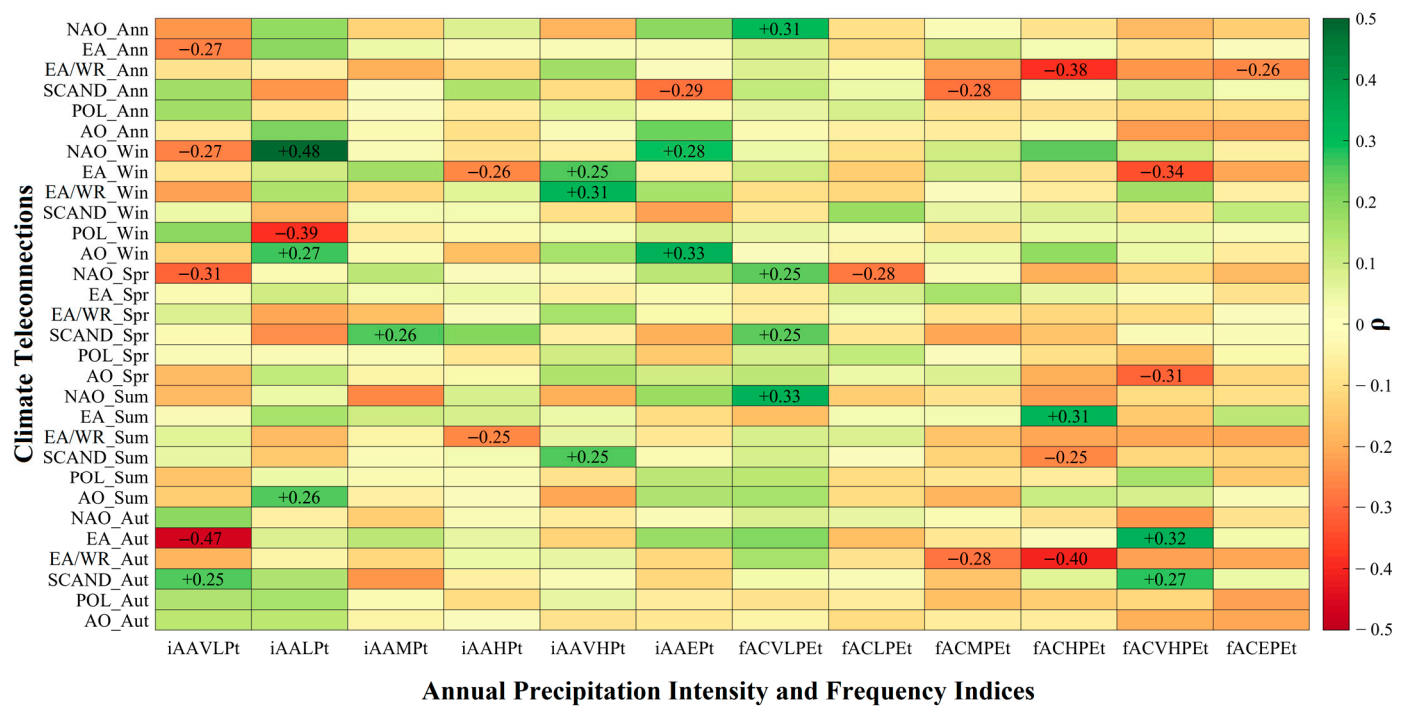


Figure 3. Normalized (% per year, $p < 0.05$) inter-annual trends in daily precipitation (a) intensity and (b) frequency indices (Table 3) at the Sodankylä, Kajaani, and Kaisaniemi stations in northern, central, and southern Finland, respectively, during the period 1909–2023. The median values for normalized trends in annual indices at each studied station are presented on the top or bottom of the bars.

In general, both iAAVLpT and fACVLPEt indices showed statistically significant ($p < 0.05$) relationships with the SCAND pattern at Sodankylä (Figure 4) and Kajaani (Figure 5), while with the EA at Kaisaniemi (Figure 6). Both the intensity (iAALpT) and frequency (fACLPEt) of light daily precipitation events were negatively associated with the NAO index at all three stations studied (Figures 4–6). However, the SCAND, EA/WR, and NAO were the influential climate teleconnections for variations in both iAAMPt and fACMPEt indices at Sodankylä (Figure 4), Kajaani (Figure 5), and Kaisaniemi (Figure 6). For heavy daily precipitation events, both the intensity (iAAHpT) and frequency (fACHPEt) were in significantly negative correlations with the EA/WR at Sodankylä (Figure 4), Kajaani (Figure 5), and Kaisaniemi (Figure 6). At all these stations, however, the very heavy daily precipitation intensity (iAAVHpT) and frequency (fACVHPet) indices showed positive relationships with the SCAND pattern (Figures 4–6). These teleconnections (the EA/WR and the SCAND) also controlled interannual variations in the intensity (iAAEPt) and frequency (fACEPEt) of extreme daily precipitation at the Sodankylä (Figure 4), Kajaani (Figure 5), and Kaisaniemi (Figure 6) stations. Figures 4–6 comprehensively represent the correlations of interannual variations in daily graded precipitation indices with the annual and seasonal large-scale climate teleconnections at the Sodankylä, Kajaani, and Kaisaniemi stations, respectively.



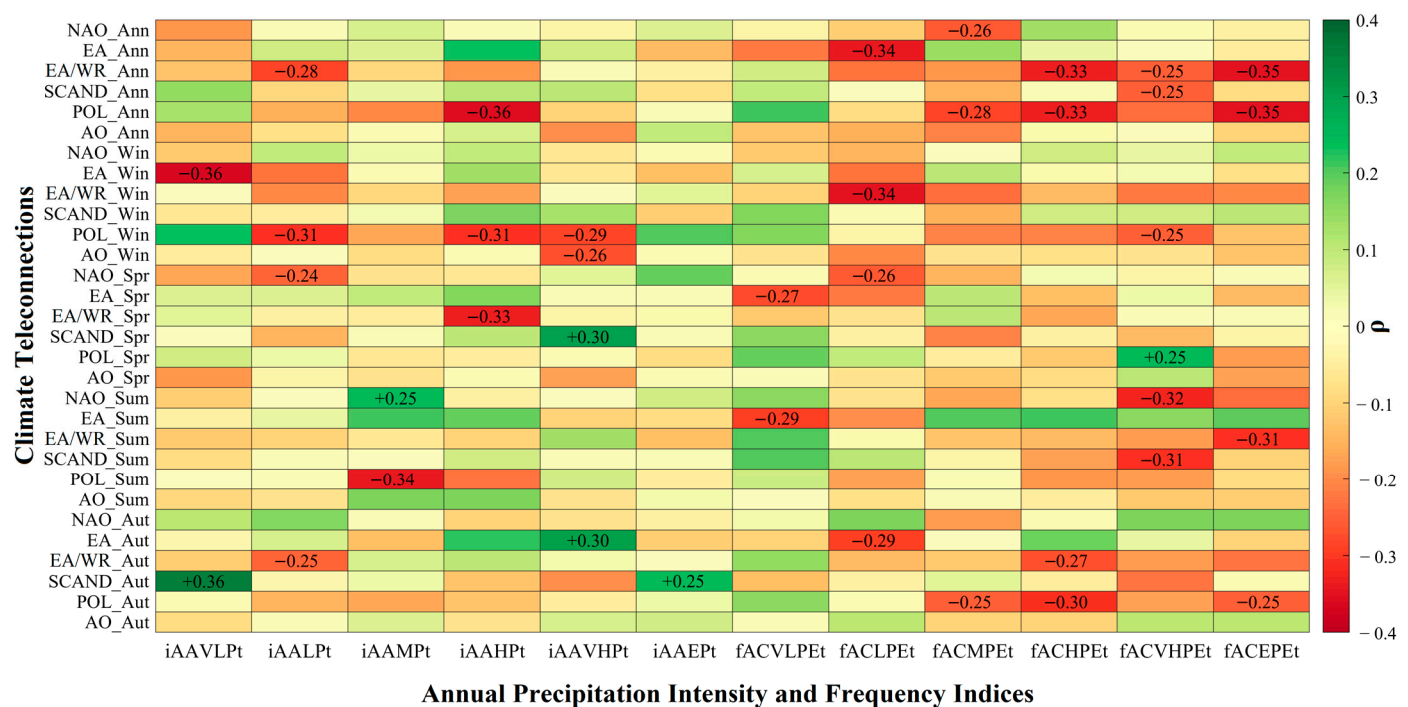


Figure 6. The Spearman's rank correlations (ρ) of annual precipitation intensity and frequency indices (Table 3) with the annual and seasonal climate teleconnections at the Kaisaniemi station in southern Finland during the period 1951–2023. The written values show statistically significant ($p < 0.05$) correlations.

4. Discussion

4.1. Variability and Trends in Graded Daily Precipitation Characteristics

In Finland, daily precipitation intensity [42] and all extreme precipitation intensity indices [20] generally decrease from the northern to southern parts. The present study also found this spatial pattern in the intensity of graded daily precipitation events, except for both very light and moderate daily precipitation records that showed the highest amounts in central Finland. Such disagreement might be related to the different definitions used by these studies to calculate extreme daily precipitation intensities in Finland. In fact, applying percentiles by previous studies focusing on EPEs resulted in a similar spatial pattern to the mean precipitation variability across the country. Using different absolute daily precipitation amount boundaries, however, the present study improved our knowledge about which grades of daily precipitation intensity behave differently from the spatial distribution of precipitation values throughout Finland previously reported.

Defining the EPEs based on different percentile values, ref. [42] concluded that the extreme precipitation frequency increased from southern to northern Finland. However, ref. [20] determined that both relatively low and high extreme precipitation indices were more frequent in northern and southern Finland, respectively, during the period 1961–2011. The present study also indicated more frequencies of relatively low (high) EPEs in the north (south) than in the south (north) of Finland. As exceptions, we found the highest rates of frequency for both light and extreme daily precipitation grades at the Kajaani station in central Finland. Similarly, a few previous studies also reported such higher return values for relatively high EPEs in central Finland than in its other areas [62,63].

The present study detected statistically significant decreasing trends in the intensity of very light daily precipitation grades at all three hydrometeorological stations of Kaisaniemi, Kajaani, and Sodankyl in southern, central, and northern Finland, respectively, during the last 115 years (1909–2023). For the same stations, our previous study also reported such significant decreases in the very light amounts of daily precipitation calculated based on their 50th percentile values [42]. Both of these studies determined the highest rate of

such decreasing trends at the Sodankylä station in northern Finland. The lowest rates of such decreasing trends were found at Kaisaniemi in southern areas by our previous study [42] but at Kajaani in central parts by the present study. Similarly, [63] concluded substantial decreases in the moderate amounts of daily precipitation, defined based on their 60th percentile values, in Finland. Additionally, the present study found considerable decreasing (increasing) trends in light and moderate (very heavy) daily precipitation grades at Kajaani and Kaisaniemi (Kajaani) in central and southern (central) Finland, respectively, during the period 1909–2023. Such decreases, however, were not reported by previous studies. This might likely be related to the use of other hydrometeorological stations throughout Finland, the consideration of different study periods, and the application of dissimilar definitions for calculating EPEs. Like [42,63], moreover, the present study identified that heavy to extreme daily precipitation grades were mostly unchanged in Finland over time.

We found significant increasing trends in the frequency of very light precipitation grade in Finland during the period 1909–2023. The highest and lowest rates of these increases were seen in the north and south of this country, respectively. Such increasing trends and their spatial patterns throughout Finland were also reported previously by [42]. Despite such increases, the present study detected considerable decreasing trends in moderate and heavy (extreme) daily precipitation grades at Kajaani (Kaisaniemi) in central (southern) Finland over time. Less frequent moderate precipitation at Kajaani was similarly identified by our previous study [42]. When analyzing extreme precipitation indices, however, [20] showed no clear changes in the number of heavy (daily precipitation ≥ 10 mm) and very heavy (daily precipitation ≥ 20 mm) days, but it showed significant increases in wet days (daily precipitation ≥ 1 mm) in Finland during the period 1961–2011. At Kaisaniemi, Kajaani, and Sodankylä, no significant trends in heavy precipitation days were detected during the period 1910–1995 [64]. The other previous studies reported increases in very heavy precipitation frequency over Finland during the 20th century, particularly after 1980 [12,65]. The differences between our results and such previous studies are mainly because of the grading of daily precipitation records by the present study, which can provide us with more details about which amount boundaries of daily precipitation significantly contributed to changes in the frequency of EPEs greater than a certain threshold (e.g., 1 mm).

4.2. Influential Climate Teleconnections

Across Finland, historical variations in annual precipitation were considerably associated with the SCAND and EA/WR patterns in 1911–2011 [39]. Statistically significant correlations between both the SCAND and EA/WR patterns and the ratio of annual total precipitation to the number of days with precipitation (>0 mm) were also reported over Finland during the period 1908–2008 [42]. By analyzing extreme precipitation indices, similarly, ref. [20] concluded that the SCAND and EA/WR were the most influential climate teleconnections for interannual variability in total precipitation in wet days in Finland through the years 1961–2011. Likewise, the present study found substantial relationships between these two climate teleconnections—SCAND and EA/WR—and both the intensities and frequencies of moderate, heavy, very heavy, and extreme precipitation records, which are key components of annual precipitation in Finland. Additionally, this study discovered that the SCAND could also influence very light daily precipitation (between 0 and 1 mm) across the country, while the light daily precipitation (between 1 and 5 mm) was more evidently connected to the NAO during the period 1951–2023. This can be explained by the typical occurrence of very light (light) daily precipitation events during all months (cold months: December–May) of the year, for which the SCAND (NAO) generally influences precipitation variability across Finland [20,39]. Although our previous studies reported such relationships between climate teleconnections and EPEs in Finland, the present study improved our understating about the roles of the SCAND, EA/WR, and NAO in the spatio-

temporal variations in different daily precipitation grades as the primary contributors to the formation of EPEs across the country—an insight that has not yet been acknowledged.

The SCAND consists of a primary circulation center over the Scandinavian Peninsula and an extensive part of the Arctic Ocean throughout northern Siberia [48]. With the opposite sign of pressure anomalies, the two other action centers of this climate teleconnection (SCAND) are located over western Europe (the north-east Atlantic) and Mongolia (western China) [48]. The negative/positive phase of SCAND describes low/high pressure airflow inducing a colder/warmer and wetter/drier climate than normal conditions over Greenland, the Norwegian Sea, and the Scandinavian Peninsula [50]. This negative relationship was also evidenced by significant decreases in very light precipitation amounts in Finland, which were positively associated with the SCAND variability over time. However, considerable correlations between the SCAND and moderate, very heavy, and extreme daily precipitation events were not caused by any significant changes in their historical time series.

For Finland, the EA/WR describes the meridional circulation that naturally weakens when the westerly airflow strengthens. As a zonally oriented climate teleconnection, the EA/WR principally consists of two action centers over western Europe and the Caspian Sea in winter, while the other three pressure anomaly centers are in the coastal areas of Portugal, northwestern Europe, and the western–northwestern parts of Russia during both spring and autumn seasons [48]. The negative/positive phase of this climate teleconnection (EA/WR) is fundamentally associated with the southeasterly/northwesterly and southerly/northerly airflows over the Baltic Sea and the East European Plain [49]. Accordingly, the positive phase of EA/WR principally brings a warmer and wetter (colder and drier) climate than normal conditions across East Asia (the Arctic area, large parts of western Russia, and northeast Africa) [49]. This study confirmed such relationships by measuring significant negative correlations between increasing EA/WR values [66] and heavy daily precipitation events, resulting in their lower frequency at the Kajaani station located close to western Russia in recent decades.

Besides such effects of SCAND (EA/WR) on very light, moderate, very heavy, and extreme (heavy) daily precipitation, this study also determined the substantial negative correlations of NAO with both the intensity and frequency of light daily precipitation records in Finland. This climate teleconnection (NAO) is a numeric index for describing the power of westerlies from the North Atlantic to the Atlantic parts of Europe [47]. Hence, the positive/negative NAO phase generally corresponds to the strengthening and weakening of westerly airflows, bringing a milder and wetter/colder and drier climate than normal conditions over the north of Europe, particularly during the cold months (Dec–May) [67,68]. Based on [69], the NAO power increased by 0.20 decade⁻¹ in recent decades. Despite significant negative relationships between this climate teleconnection (NAO) and light daily precipitation events, such an increasing trend in the NAO caused no clear changes in the intensity and frequency of this daily precipitation grade (light) across Finland. As the only exception, however, the Kajaani station in central Finland experienced a significant decreasing trend in the intensity of light daily precipitation over time.

5. Conclusions

This study analyzed variability and trends in daily graded (from very light to extreme) precipitation records at three hydrometeorological stations of Kaisaniemi, Kajaani, and Sodankylä in southern, central, and northern Finland during the last 115 years (1909–2023). The relationships of such variability and trends with large-scale, well-known climate teleconnections were also measured for the period of 1951–2023. The major conclusions were:

- In general, more intense but less frequent very light daily precipitation events were recorded in Finland during the period 1909–2023. The Sodankylä (Kaisaniemi) station in northern (southern) Finland experienced the highest (lowest) rates of such decreases and increases in the intensity and frequency of historical very light precipitation events. At Kajaani in central Finland, however, the intensities of light daily precipitation events

showed a significant decreasing trend during the period 1909–2023. At this station, statistically significant trends were also detected in both the intensity and frequency of heavy daily precipitation events over time.

- The SCAND (EA) pattern was the strongest climate teleconnection positively (negatively) influencing the variability in both the intensity and frequency of very light daily events in northern and central (southern) Finland during the period 1951–2023. At all three stations of Sodankylä, Kajaani, and Kaisaniemi, however, both the intensity and frequency of light daily precipitation events showed substantial negative relationships with the NAO in the last 70 years. The SCAND and NAO also influenced the variations in both the intensity and frequency of historical moderate daily precipitation events at all three stations studied. The intensities and frequencies of all heavy (very heavy and extreme) daily precipitation events in Finland, however, were mainly controlled by variations in the EA/WR (SCAND) pattern over time. Hence, the SCAND was the most influential climate teleconnection for variations in both the intensities and frequencies of all daily graded precipitation events in Finland, except for light daily precipitation records significantly associated with the NAO over time.

Such conclusions can lay the foundation for developing adaptation and mitigation strategies for sustainable water resources management in the boreal environment of Finland and supporting this country in achieving economic, social, and environmental sustainability under global warming and climate change.

Author Contributions: Conceptualization, M.I. and Z.A.; methodology, M.I., Z.A. and R.A.; software, R.A. and F.A.; validation, F.A. and G.S.; formal analysis, M.I., G.S. and H.A.; investigation, M.I., Z.A. and H.A.; resources, M.I.; data curation, Z.A. and R.A.; writing—original draft preparation, M.I., Z.A. and R.A.; writing—review and editing, M.I.; visualization, M.I., Z.A. and F.A.; supervision, M.I.; project administration, M.I.; funding acquisition, M.I. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by the Sakari Alhopuro Foundation (Grant Nos. 20220247 and 20230218) and the Maa- ja vesi tekniikan tuki r.y. (Grant Nos. 44008 and 45599).

Data Availability Statement: All datasets analyzed during this study are publicly available through the references given in the manuscript.

Acknowledgments: We would like to acknowledge the Finnish Meteorological Institute (FMI) for recording historical daily SAT and precipitation in Finland and the Finnish Environment Institute (SYKE) at the hydrometeorological measurement stations studied. We are also grateful to the Climate Prediction Center (CPC) at the National Oceanic and Atmospheric Administration (NOAA) of the United States for making available online the standardized monthly values of climate teleconnections used in this study.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. IPCC; Masson-Delmotte, V.; Zhai, P.; Pirani, A.; Connors, S.L.; Péan, C.; Berger, S.; Caud, N.; Chen, Y.; Goldfarb, L.; et al. *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*; Intergovernmental Panel on Climate Change: Geneva, Switzerland, 2021.
2. Iz, H.B. Is the Global Sea Surface Temperature Rise Accelerating? *Geod. Geodyn.* **2018**, *9*, 432–438. [[CrossRef](#)]
3. Ali, H.; Mishra, V. Contrasting Response of Rainfall Extremes to Increase in Surface Air and Dewpoint Temperatures at Urban Locations in India. *Sci. Rep.* **2017**, *7*, 1228. [[CrossRef](#)] [[PubMed](#)]
4. Kirchmeier-Young, M.C.; Zhang, X. Human Influence Has Intensified Extreme Precipitation in North America. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 13308–13313. [[CrossRef](#)] [[PubMed](#)]
5. Tabari, H.; Madani, K.; Willems, P. The Contribution of Anthropogenic Influence to More Anomalous Extreme Precipitation in Europe. *Environ. Res. Lett.* **2020**, *15*, 104077. [[CrossRef](#)]
6. Irannezhad, M.; Liu, J.; Chen, D. Extreme Precipitation Variability across the Lancang-Mekong River Basin during 1952–2015 in Relation to Teleconnections and Summer Monsoons. *Int. J. Climatol.* **2022**, *42*, 2614–2638. [[CrossRef](#)]
7. Liu, A.; Soneja, S.I.; Jiang, C.; Huang, C.; Kerns, T.; Beck, K.; Mitchell, C.; Sapkota, A. Frequency of Extreme Weather Events and Increased Risk of Motor Vehicle Collision in Maryland. *Sci. Total Environ.* **2017**, *580*, 550–555. [[CrossRef](#)]

8. Ohba, M.; Sugimoto, S. Differences in Climate Change Impacts between Weather Patterns: Possible Effects on Spatial Heterogeneous Changes in Future Extreme Rainfall. *Clim. Dyn.* **2019**, *52*, 4177–4191. [\[CrossRef\]](#)
9. Rummukainen, M. Changes in Climate and Weather Extremes in the 21st Century. *WIREs Clim. Chang.* **2012**, *3*, 115–129. [\[CrossRef\]](#)
10. Donat, M.G.; Alexander, L.V.; Yang, H.; Durre, I.; Vose, R.; Dunn, R.J.H.; Willett, K.M.; Aguilar, E.; Brunet, M.; Caesar, J.; et al. Updated Analyses of Temperature and Precipitation Extreme Indices since the Beginning of the Twentieth Century: The HadEX2 Dataset. *J. Geophys. Res. Atmos.* **2013**, *118*, 2098–2118. [\[CrossRef\]](#)
11. Liu, B.; Tan, X.; Gan, T.Y.; Chen, X.; Lin, K.; Lu, M.; Liu, Z. Global Atmospheric Moisture Transport Associated with Precipitation Extremes: Mechanisms and Climate Change Impacts. *WIREs Water* **2020**, *7*, e1412. [\[CrossRef\]](#)
12. Alexander, L.V.; Zhang, X.; Peterson, T.C.; Caesar, J.; Gleason, B.; Klein Tank, A.M.G.; Haylock, M.; Collins, D.; Trewin, B.; Rahimzadeh, F.; et al. Global Observed Changes in Daily Climate Extremes of Temperature and Precipitation. *J. Geophys. Res. Atmos.* **2006**, *111*, D05109. [\[CrossRef\]](#)
13. Zhang, X.; Alexander, L.; Hegerl, G.C.; Jones, P.; Tank, A.K.; Peterson, T.C.; Trewin, B.; Zwiers, F.W. Indices for Monitoring Changes in Extremes Based on Daily Temperature and Precipitation Data. *WIREs Clim. Chang.* **2011**, *2*, 851–870. [\[CrossRef\]](#)
14. Serinaldi, F.; Kilsby, C.G. Stationarity Is Undead: Uncertainty Dominates the Distribution of Extremes. *Adv. Water Resour.* **2015**, *77*, 17–36. [\[CrossRef\]](#)
15. Kim, H.; Kim, S.; Shin, H.; Heo, J.-H. Appropriate Model Selection Methods for Nonstationary Generalized Extreme Value Models. *J. Hydrol.* **2017**, *547*, 557–574. [\[CrossRef\]](#)
16. Liu, S.; Huang, S.; Huang, Q.; Xie, Y.; Leng, G.; Luan, J.; Song, X.; Wei, X.; Li, X. Identification of the Non-Stationarity of Extreme Precipitation Events and Correlations with Large-Scale Ocean-Atmospheric Circulation Patterns: A Case Study in the Wei River Basin, China. *J. Hydrol.* **2017**, *548*, 184–195. [\[CrossRef\]](#)
17. Fu, J.; Qian, W.; Lin, X.; Chen, D. Trends in Graded Precipitation in China from 1961 to 2000. *Adv. Atmos. Sci.* **2008**, *25*, 267–278. [\[CrossRef\]](#)
18. Hu, M.; Dong, M.; Tian, X.; Wang, L.; Jiang, Y. Trends in Different Grades of Precipitation over the Yangtze River Basin from 1960 to 2017. *Atmosphere* **2021**, *12*, 413. [\[CrossRef\]](#)
19. Xie, M.; Ren, Z.; Li, Z.; Zhang, X.; Ma, X.; Li, P.; Shen, Z. Evolution of the Precipitation–Stream Runoff Relationship in Different Precipitation Scenarios in the Yellow River Basin. *Urban Clim.* **2023**, *51*, 101609. [\[CrossRef\]](#)
20. Irannezhad, M.; Chen, D.; Kløve, B.; Moradkhani, H. Analysing the Variability and Trends of Precipitation Extremes in Finland and Their Connection to Atmospheric Circulation Patterns. *Int. J. Climatol.* **2017**, *37*, 1053–1066. [\[CrossRef\]](#)
21. Pedretti, D.; Irannezhad, M. Non-Stationary Peaks-over-Threshold Analysis of Extreme Precipitation Events in Finland, 1961–2016. *Int. J. Climatol.* **2019**, *39*, 1128–1143. [\[CrossRef\]](#)
22. Liu, Y.; Zhang, C.; Tang, Q.; Hosseini-Moghari, S.-M.; Haile, G.G.; Li, L.; Li, W.; Yang, K.; van der Ent, R.J.; Chen, D. Moisture Source Variations for Summer Rainfall in Different Intensity Classes over Huaihe River Valley, China. *Clim. Dyn.* **2021**, *57*, 1121–1133. [\[CrossRef\]](#)
23. Pathak, A.; Ghosh, S.; Martinez, J.A.; Dominguez, F.; Kumar, P. Role of Oceanic and Land Moisture Sources and Transport in the Seasonal and Interannual Variability of Summer Monsoon in India. *J. Clim.* **2017**, *30*, 1839–1859. [\[CrossRef\]](#)
24. Jiang, Z.; Jiang, S.; Shi, Y.; Liu, Z.; Li, W.; Li, L. Impact of Moisture Source Variation on Decadal-Scale Changes of Precipitation in North China from 1951 to 2010. *J. Geophys. Res. Atmos.* **2017**, *122*, 600–613. [\[CrossRef\]](#)
25. Zhu, Y.; Sang, Y.-F.; Chen, D.; Sivakumar, B.; Li, D. Effects of the South Asian Summer Monsoon Anomaly on Interannual Variations in Precipitation over the South-Central Tibetan Plateau. *Environ. Res. Lett.* **2020**, *15*, 124067. [\[CrossRef\]](#)
26. Chen, D.; Chen, Y. Association between Winter Temperature in China and Upper Air Circulation over East Asia Revealed by Canonical Correlation Analysis. *Glob. Planet. Change* **2003**, *37*, 315–325. [\[CrossRef\]](#)
27. Glantz, M.H.; Katz, R.; Nicholls, N. (Eds.) *Teleconnections Linking Worldwide Climate Anomalies: Scientific Basis and Societal Impact*; Cambridge University Press: Cambridge, UK, 2009; ISBN 9780521106849, 0521106842.
28. Wang, B.; Lee, M.-Y.; Xie, Z.; Lu, M.; Pan, M. A New Asian/North American Teleconnection Linking Clustered Extreme Precipitation from Indian to Canada. *NPJ Clim. Atmos. Sci.* **2022**, *5*, 90. [\[CrossRef\]](#)
29. Zhang, X.; Chen, Y.; Fang, G.; Li, Y.; Li, Z.; Wang, F.; Xia, Z. Observed Changes in Extreme Precipitation over the Tianshan Mountains and Associated Large-Scale Climate Teleconnections. *J. Hydrol.* **2022**, *606*, 127457. [\[CrossRef\]](#)
30. Kang, X.; Min, R.; Dai, J.; Gu, X. The Role of Teleconnection in the Occurrence Probability of Extreme Precipitation over China Based on Extreme Value Theory. *Front. Environ. Sci.* **2022**, *10*, 1013636. [\[CrossRef\]](#)
31. Biswas, J. Unravelling the Influence of Teleconnection Patterns on Monsoon Extreme Precipitation Indices over the Sikkim Himalayas and West Bengal. *J. Hydrol.* **2023**, *618*, 129148. [\[CrossRef\]](#)
32. Ghasemifar, E.; Irannezhad, M.; Minaei, F.; Minaei, M. The Role of ENSO in Atmospheric Water Vapor Variability during Cold Months over Iran. *Theor. Appl. Climatol.* **2022**, *148*, 795–817. [\[CrossRef\]](#)
33. Irannezhad, M.; Ahmadi, B.; Liu, J.; Chen, D.; Matthews, J.H. Global Water Security: A Shining Star in the Dark Sky of Achieving the Sustainable Development Goals. *Sustain. Horiz.* **2022**, *1*, 100005. [\[CrossRef\]](#)
34. Nations, United. *About the Sustainable Development Goals—United Nations Sustainable Development*; United Nations Development Programme: New York, NY, USA, 2015.

35. Chen, D.; Chen, H.W. Using the Köppen Classification to Quantify Climate Variation and Change: An Example for 1901–2010. *Environ. Dev.* **2013**, *6*, 69–79. [\[CrossRef\]](#)
36. Käyhkö, J. Muuttuuko Pohjolan Ilmasto? (Fennoscandian Climate in Change?). *Publ. Geogr. Dep. Univ. Turku* **2004**, *168*, 19–35.
37. Peel, M.C.; Finlayson, B.L.; McMahon, T.A. Updated World Map of the Köppen-Geiger Climate Classification. *Hydrol. Earth Syst. Sci.* **2007**, *11*, 1633–1644. [\[CrossRef\]](#)
38. Irannezhad, M.; Chen, D.; Kløve, B. Interannual Variations and Trends in Surface Air Temperature in Finland in Relation to Atmospheric Circulation Patterns, 1961–2011. *Int. J. Climatol.* **2015**, *35*, 3078–3092. [\[CrossRef\]](#)
39. Irannezhad, M.; Marttila, H.; Kløve, B. Long-Term Variations and Trends in Precipitation in Finland. *Int. J. Climatol.* **2014**, *34*, 3139–3153. [\[CrossRef\]](#)
40. Jokinen, P.; Kaukoranta, J.-P.; Kangas, A.; Alenius, P.; Eriksson, P.; Johansson, M.; Wilkman, S. *Tilastoja Suomen Ilmastosta ja Merestä 1991–2020*; Finnish Meteorological Institute: Helsinki, Finland, 2021.
41. Irannezhad, M.; Ronkanen, A.K.; Kløve, B. Effects of Climate Variability and Change on Snowpack Hydrological Processes in Finland. *Cold Reg. Sci. Technol.* **2015**, *118*, 14–29. [\[CrossRef\]](#)
42. Irannezhad, M.; Marttila, H.; Chen, D.; Kløve, B. Century-Long Variability and Trends in Daily Precipitation Characteristics at Three Finnish Stations. *Adv. Clim. Chang. Res.* **2016**, *7*, 54–69. [\[CrossRef\]](#)
43. Irannezhad, M.; Ronkanen, A.-K.; Kløve, B. Wintertime Climate Factors Controlling Snow Resource Decline in Finland. *Int. J. Climatol.* **2016**, *36*, 110–131. [\[CrossRef\]](#)
44. Solantie, R.; Junila, P. *Sademäärien Korjaaminen Tretjakovin Ja Wildin Sademittarien Vertailumittausten Avulla, Summary in English: The Correction of Precipitation Measurements Based on Comparisons between Tretyakov and Wild Gauges*; Finnish Meteorological Institute: Helsinki, Finland, 1995.
45. Irannezhad, M.; Torabi Haghighi, A.; Chen, D.; Kløve, B. Variability in Dryness and Wetness in Central Finland and the Role of Teleconnection Patterns. *Theor. Appl. Climatol.* **2015**, *122*, 471–486. [\[CrossRef\]](#)
46. Irannezhad, M.; Chen, D.; Kløve, B. The Role of Atmospheric Circulation Patterns in Agroclimate Variability in Finland, 1961–2011. *Geogr. Ann. Ser. A, Phys. Geogr.* **2016**, *98*, 287–301. [\[CrossRef\]](#)
47. Thompson, D.W.J.; Wallace, J.M. The Arctic Oscillation Signature in the Wintertime Geopotential Height and Temperature Fields. *Geophys. Res. Lett.* **1998**, *25*, 1297–1300. [\[CrossRef\]](#)
48. Barnston, A.G.; Livezey, R.E. Classification, Seasonality and Persistence of Low-Frequency Atmospheric Circulation Patterns. *Mon. Weather Rev.* **1987**, *115*, 1083–1126. [\[CrossRef\]](#)
49. Lim, Y.K.; Kim, H.D. Impact of the Dominant Large-Scale Teleconnections on Winter Temperature Variability over East Asia. *J. Geophys. Res. Atmos.* **2013**, *118*, 7835–7848. [\[CrossRef\]](#)
50. Bueh, C.; Nakamura, H. Scandinavian Pattern and Its Climatic Impact. *Q. J. R. Meteorol. Soc.* **2007**, *133*, 2117–2131. [\[CrossRef\]](#)
51. Mann, H.B. Non-Parametric Test Against Trend. *Econometrica* **1945**, *13*, 245–259. [\[CrossRef\]](#)
52. Kendall, M.G. *Rank Correlation Methods*; Oxford University Press: Oxford, UK, 1948.
53. Yue, S.; Pilon, P.; Phinney, B.; Cavadias, G. The Influence of Autocorrelation on the Ability to Detect Trend in Hydrological Series. *Hydrol. Process.* **2002**, *16*, 1807–1829. [\[CrossRef\]](#)
54. Sen, P.K. Estimates of the Regression Coefficient Based on Kendall’s Tau. *J. Am. Stat. Assoc.* **1968**, *63*, 1379–1389. [\[CrossRef\]](#)
55. Helsel, D.R.; Hirsch, R.M. *Statistical Methods in Water Resources*; U.S. Geological Survey: Reston, VA, USA, 1992.
56. Park, E.; Lee, Y.J. Estimates of Standard Deviation of Spearman’s Rank Correlation Coefficients with Dependent Observations. *Commun. Stat. Part B Simul. Comput.* **2001**, *30*, 129–142. [\[CrossRef\]](#)
57. Irannezhad, M.; Kløve, B. Do Atmospheric Teleconnection Patterns Explain Variations and Trends in Thermal Growing Season Parameters in Finland? *Int. J. Climatol.* **2015**, *35*, 4619–4630. [\[CrossRef\]](#)
58. Kiani, S.; Irannezhad, M.; Ronkanen, A.-K.; Moradkhani, H.; Kløve, B. Effects of Recent Temperature Variability and Warming on the Oulu-Hailuoto Ice Road Season in the Northern Baltic Sea. *Cold Reg. Sci. Technol.* **2018**, *151*, 1–8. [\[CrossRef\]](#)
59. Irannezhad, M.; Liu, J.; Chen, D. Influential Climate Teleconnections for Spatiotemporal Precipitation Variability in the Lancang-Mekong River Basin from 1952 to 2015. *J. Geophys. Res. Atmos.* **2020**, *125*, e2020JD033331. [\[CrossRef\]](#)
60. Irannezhad, M.; Abdullah Abdulghafour, Z.; Marttila, H. Annual and Seasonal Mean Daily Discharge in Natural and Regulated Rivers in Northern Finland: Variability, Trends, and Links to Climate Teleconnections. *Hydrol. Res.* **2024**, nh2024041. [\[CrossRef\]](#)
61. Irannezhad, M.; Abdulghafour, Z.; Sadeqi, A. Climate Teleconnections Influencing Historical Variations, Trends, and Shifts in Snow Cover Days in Finland. In *Earth Systems and Environment*; Springer: Berlin/Heidelberg, Germany, 2024. [\[CrossRef\]](#)
62. Venäläinen, A.; Jylhä, K.; Kilpeläinen, T.; Saku, S.; Tuomenvirta, H.; Vajda, A.; Ruosteenoja, K. Recurrence of Heavy Precipitation, Dry Spells and Deep Snow Cover in Finland Based on Observations. *Boreal Environ. Res.* **2009**, *14*, 166–172.
63. Wen, G.; Huang, G.; Hu, K.; Qu, X.; Tao, W.; Gong, H. Changes in the Characteristics of Precipitation over Northern Eurasia. *Theor. Appl. Climatol.* **2015**, *119*, 653–665. [\[CrossRef\]](#)
64. Heino, R.; Brázdil, R.; Førland, E.; Tuomenvirta, H.; Alexandersson, H.; Beniston, M.; Pfister, C.; Rebetez, M.; Rosenhagen, G.; Rösner, S.; et al. Progress in the Study of Climatic Extremes in Northern and Central Europe. *Clim. Change* **1999**, *42*, 151–181. [\[CrossRef\]](#)
65. Groisman, P.Y.; Knight, R.W.; Easterling, D.R.; Karl, T.R.; Hegerl, G.C.; Razuvaev, V.N. Trends in Intense Precipitation in the Climate Record. *J. Clim.* **2005**, *18*, 1326–1350. [\[CrossRef\]](#)

66. Krichak, S.O.; Kishcha, P.; Alpert, P. Decadal Trends of Main Eurasian Oscillations and the Eastern Mediterranean Precipitation. *Theor. Appl. Climatol.* **2002**, *72*, 209–220. [[CrossRef](#)]
67. Gormsen, A.K.; Hense, A.; Toldam-Andersen, T.B.; Braun, P. Large-Scale Climate Variability and Its Effects on Mean Temperature and Flowering Time of Prunus and Betula in Denmark. *Theor. Appl. Climatol.* **2005**, *82*, 41–50. [[CrossRef](#)]
68. Jaagus, J. Climatic Changes in Estonia during the Second Half of the 20th Century in Relationship with Changes in Large-Scale Atmospheric Circulation. *Theor. Appl. Climatol.* **2006**, *83*, 77–88. [[CrossRef](#)]
69. Wang, D.; Wang, C.; Yang, X.; Lu, J. Winter Northern Hemisphere Surface Air Temperature Variability Associated with the Arctic Oscillation and North Atlantic Oscillation. *Geophys. Res. Lett.* **2005**, *32*, L16706.1–L16706.4. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.



Society of Petroleum Engineers

SPE-223268-MS

Reconstructing Missing and Non-Recorded Well Log Data Using Machine Learning Techniques.

K. W. Amadi, R. M Elgaddafi, M. A AlAli, and A. M Dashti, Petroleum Engineering Department, Australian University, Kuwait City, Kuwait.

Copyright 2024, Society of Petroleum Engineers DOI [10.2118/223268-MS](https://doi.org/10.2118/223268-MS)

This paper was prepared for presentation at the Mediterranean Offshore Conference held in Alexandria, Egypt, 20 - 22 October 2024.

This paper was selected for presentation by an SPE program committee following review of information contained in an abstract submitted by the author(s). Contents of the paper have not been reviewed by the Society of Petroleum Engineers and are subject to correction by the author(s). The material does not necessarily reflect any position of the Society of Petroleum Engineers, its officers, or members. Electronic reproduction, distribution, or storage of any part of this paper without the written consent of the Society of Petroleum Engineers is prohibited. Permission to reproduce in print is restricted to an abstract of not more than 300 words; illustrations may not be copied. The abstract must contain conspicuous acknowledgment of SPE copyright.

Abstract

Petrophysical estimation of rocks are carried out for lithologic characterization and to quantify the reservoir hydrocarbon prospects. During drilling operation, the continuous recording of well log data is performed using Logging Whilst Drilling (LWD) tools and sometimes the LWD tool failure results in loss of data especially when decision was made to drill ahead due to project economics resulting in gaps or unrecorded data. This study is aimed at using Machine Learning (ML) techniques in predicting missing and unrecorded data using offsets well data. During the study detailed literature review addressing current industry trends in the handling gaps in petrophysical log were reviewed, then four ML models were trained and used in predicting lost data entries using offsets well log data. The models utilized comprised CatBoost (CB), Gradient boost (GB), Random Forest (RF) and Support Vector Machine (SVR). The ML algorithms were first trained with 21595 data points using a 70:30 percentage ratio for training and testing respectively. After that, 8650 data points from a different well were used to validate the developed model. The real-time drilling parameters required as input data includes Gamma ray (GR), neutron (NPHI), bulk density (RHOB), photoelectric absorption factor (PEF), the borehole diameter, (CALI). The modeling result showed a good match between the actual and predicted (logs) with coefficients of determination for training and testing dataset of 0.99 and 0.97 for CatBoost and RF respectively which are the two best predictors. The main added value of this approach is that the input drilling parameters are readily available in real-time and can timely aid in well placement decisions which improves the productivity of the well.

Keywords: Machine Learning, Petrophysical logs, unrecorded data, Log reconstruction, Predictive analytics

Introduction

Geophysical research uses statistical and mathematical techniques to extract information about subsurface properties of rock, particularly through the use of well logs. which plays a crucial role in characterizing subsurface reservoirs, particularly in the domain of oil and gas exploration to aid in identifying commercial reserves accumulation (McNamara and McKenzie-Brown, 2013). Geophysical Well logs provide detailed

information about the physical and chemical properties of sedimentary rocks, including, gamma ray intensity, porosity, electrical resistance, density, resistivity, salinity, and the types and quantities of fluids in the pores which helps in understanding the hydrocarbon productive potential (Rui and Ahpio, 2018). Usually, several logs are acquired in each well, that supplement each other's information. The log dataset information are normally collected through sensing tools that are lowered into the borehole in the bottomhole assembly (BHA) or by wireline cable. The data collected by each sensor is often recorded at the surface as the borehole is drilled or when the tool is been retrieved out hole. Fig.1 shows the well log representing the different rock stratum of the earth. In the process of well construction, there are different reasons a log dataset are lost, this includes, equipment malfunctioning, poor data acquisition, hole washed-out, tool failure and inadequate storage or incomplete logging that results in missing log data in specific areas or the entirety of the section or category from sensor failure.(Rezaee et al. 1997). Well log gaps lead to less information in which to base the geoscientific models, and consequently results in larger uncertainty in the field development decisions. According to the principles of Iceberg effect, commonly known as theory of omission, when essential information for an evaluation of a process is masked in the aggregated data or perhaps missing data, it makes it difficult to accurately assess the complexity and uncertainty associated with the assessment (Tasnia, 2021).

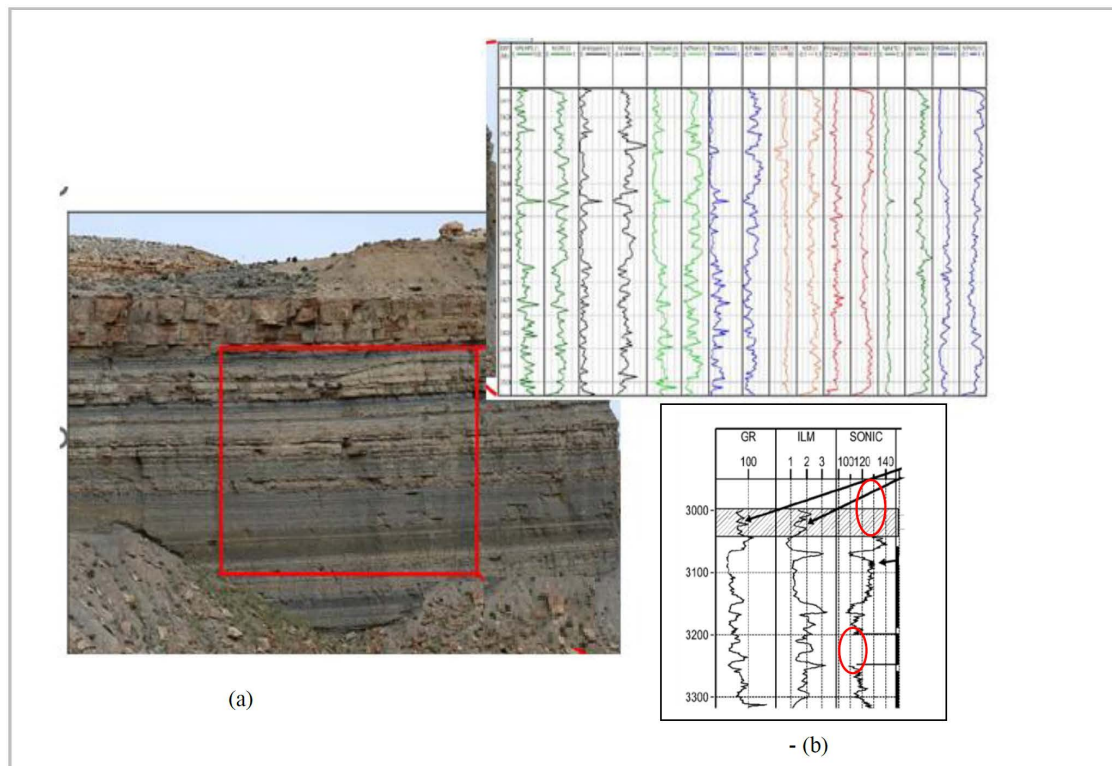


Figure 1—Well-log data representation (a) each rock stratum of the earth (Aliouane et al, 2012) (b) Well log with sonic gaps (Yu, et.al 2011)

Completing gaps in well logs can be conducted either as an imputation approach using correlation or a prediction task (Rui and

AHpio, 2018). Different techniques have been used in filling gaps or missing data in well logs including regression, deterministic petrophysical modelling, stochastic modelling, using shale matrix and fluid properties, where an estimated curve is used as input and reconstructed curve become the resultant output using different soft-computing algorithms (Aminzadeh and De Groot). This paper, therefore, presents a methodology for completing the gaps and missing data on well log using machine learning (ML) predictors

and further compares the performance accuracy of the different ML models on this prediction. The next section presents a literature review of related work addressing this problem

Literature Review

Recent studies have documented investigations on how to predict some predetermined well log data constructed on the information acquired from the other remaining sensors (Yu et al., 2011). The utilization of ML models in predicting missing log dataset promises enhanced correctness and ability to deal with a large variety of log types and geological scenarios. Nevertheless, different investigators have targeted different well log signatures and have used different algorithms as predictors. Whilst other researchers have performed comparative studies based on self-selected models on the estimation of petrophysical property of interest. According to Ouadfeul and Aliouane (2011), subsurface well-log shows a complex behavior which give the impression that suggest their fractal nature and irregular structure at scale as a result of multivariant factors that affects well log signals such as pore fluid, effective pressure, fluid saturation, pore fluid, pore shape, etc thereby limiting the applicability of linear model. A commonly used approach in the prediction tasks is based on using dataset from a single well log at close proximity as input, in order to extrapolate to a neighboring well at specific depth range in the same well (Ahmadi et al., 2014). Nonlinear machine learning models such as support vector regression (SVR), Category boost (CB), Random forest (RF) and Gradient boost (GB) have gotten recognition as the potential tool for solving nonlinear and complex problems (Hamada and Elshafei, 2010; Majdi and Beiki, 2010). Table.1 presents the summary of the description, and the ML algorithms used in this study.

Table 1—Summary of the machine learning algorithm and corresponding correlation

Model	Model Description	Correlation	Algorithm Type	Equation number
Support Vector Regression (SVR) Tipping (2001)	SVR techniques has strong nonlinear approximation capabilities. Known for excellent generalization effectiveness and does not overpredict mean values. It preserves original data variability as compared to traditional deterministic methods. It is expressed mathematical as equation (1)	$y(x) = \sum_{n=1}^N w_n K(x, x_n) + w_0$ Where w_n and w_0 represent the model 'weights and $K(x, x_n)$ represents the kernel function.	non-ensemble model	(1)
Random forest (RF) Cranganu and Breaban (2013)	The RF algorithm builds an ensemble of trees (composed of many independent decision trees), trains them, and subsequently carries out consecutive predictions with them. This helps to prevent overfitting by using bootstrap re-sampling. Bootstrap sub-sets are built on initial data with several samples replacing other repeating samples. It is expressed functional as equation (2)	$\text{Regression} = f_{rf}^B(x) = \frac{1}{B} \sum_{b=1}^B T_b(x)$ Where T_b is a random forest tree, B is the number of trees.	ensemble model	(2)
Gradient boost (GB) Liu et'al (2011)	Gradient Boost combines the tree ensemble learning and gradient descent models. It is a supervised learning algorithm that can be used for both classification and regression tasks. It is expressed mathematical as shown in equation (3)	$y_i^{(t)} = \sum_{k=1}^t f_k(x_i) = y_i^{(t-1)} + f_t(x_i)$ t =total number of base tree models, $y^{(t)}$ i = final tree model, $y^{(t-1)}$ and $f_t(x_i)$ = newly generated tree model	ensemble model	(3)
Category boost (CB) Ibrahim et'al (2020)	CB is an advanced supervised machine learning technique that uses decision trees for both classification and regression tasks. The name "CatBoost" reflects its two main features: handling categorical data directly ("Cat") and utilizing gradient boosting techniques ("Boost") as expressed in in equation (4)	$L(H) := EL(y, H(X))$	ensemble model	(4)

Helle and Bhatt (2002) proposed committee machine (CM) network for simulating the values of porosity and permeability using input data from well logs datasets such as density, sonic, neutron, gamma ray from North Sea wells. Ahmadi et'al.(2018) used several machine learning models such as genetic algorithms, Particle Swarm Optimization, Artificial Neural Networks, to predict reservoir permeability. Their results

showed that the deviation of the different models was found to be less than 1% when compared with the combined hybridized models thereby indicating the hybridized techniques for permeability and porosity can result in more reliable models. Al-Anazi and Gates, (2010) investigated the suitability of using the support vector regression (SVR) to predict reservoir porosity and permeability with small dataset from sandstone reservoir. They further compared their results with predictions from ANN model. Their findings showed that the SVR model outperformed ANN in making better predictions of the porosity and permeability. Singh et al. (2016) used artificial neural networks with back-propagation algorithm to predict the effective porosity of a gas field in Kansas. They trained the algorithm using the data-points; sonic, porosity, density and resistivity data as input. Cranganu et.al (2013) estimated sonic log disseminations in a field of the Anadarko basin, where they used the gamma-ray and deep resistivity logs as input. Two different approaches were applied to the problem, first using Gene Expression Programming (GEP) to develop the predictors, while in the second approach the authors used Support Vector Regression (SVR) to synthesize missing compressional sonic (DT) logs. They concluded that the strong nonlinear approximation abilities and generalization effectiveness of the (SVR) makes it outstanding over the traditional deterministic model. Ahmadi and Chen (2019) performed a detailed comparison of the various ML models to predict permeability of a hydrocarbon reservoir using petrophysical logs. The models used includes GA, ANN, DT, PSO and imperial competitive algorithms (ICA). In a similar vein, Wood (2020) carried out a systematic review on the Use of Machine Learning in Oil Well Petrophysics, Johnson et.al (2023) stated that a total of 104 studies have been conducted within the period of [2011-2022] with the highest number of publications in the year 2019 as shown in Fig.2a. Johnson et.al (2023), further defined the area of investigation using machine includes prediction/ forecast, characterization/classification, estimation/ calculation, comparison and optimization. The various domains and their percentages are shown Fig.2b. The review showed that most investigators used the ML for petrophysical predictions.

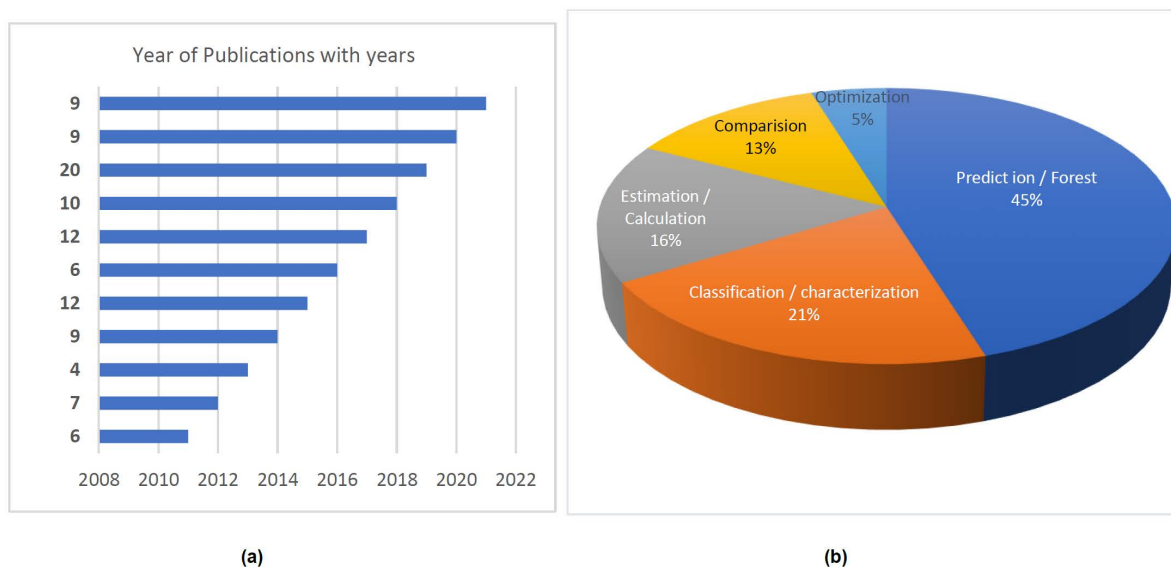


Figure 2—Use of Machine Learning in Oil Well Petrophysics (a) no. publication within the year (b) Percentage problem area investigated

In 2019, (Ahmadi and Chen 2019) conducted a comprehensive comparison of various machine-learning models to predict porosity and permeability in oil reservoirs using petrophysical logs. Their study used the following ML model; genetic algorithms (GA). artificial neural networks (ANN), fuzzy decision trees (FDT), imperial competitive algorithms (ICA), particle swarm optimization (PSO), and a combination of the listed model (hybrid model). In a similar vein, Wood (2020) introduced an optimized nearest- neighbor, ML and data-mining network to predict petrophysical properties such as porosity, permeability, and water

saturation using well-log data. He developed an effective algorithm that is able to evaluate multiple well-log curves, providing correct estimates of petrophysical predictions and valuable insights through extensive data mining. By standardizing the well-log representation and utilizing the data-matching algorithm, the network enables the estimation of effective permeability and water saturation (K_e , S_w) from data sets that incorporate standard well logs, lithofacies, and stratigraphic information. However, input of well-logged data is expensive and time-consuming. Sun et al. 2021 applied machine learning for identification of porosity and permeability while using logging while drilling tools (LWD) combined with conventional wireline logging.

This work further investigates the use of ML in the reconstruction of missing and unrecorded well log data, in addition to comparing the performance of ensemble and non-ensemble machine learning (ML) predictors in the prediction of sonic transit time well log curve using the other well log acquisition suites.

Methodology

This section presents the general overview of the research methodology. Three steps approach was used in the study, namely 1) data analysis and statistics, 2) Machine Learning modeling, 3) Prediction of sonic transit time (DT) from offset wells using ML, Fig.3 shows the generalized workflow for modeling and prediction task which will be briefly discussed. Four machine learning models were utilized (support vector regression (SVR), Random forest (RF), Category boost (CB), and Gradient boost (GB) in the prediction and their respective performance compared.

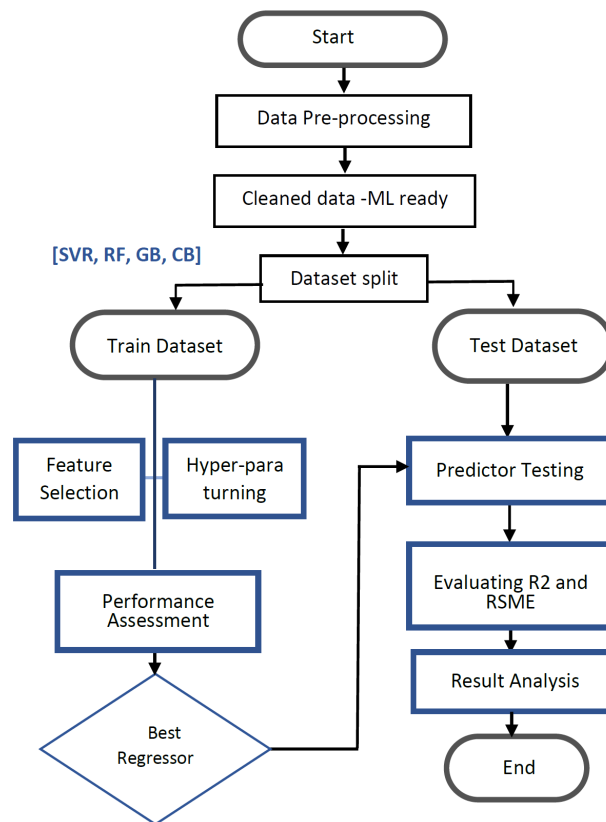


Figure 3—Methodology for ML prediction of Sonic transit time using other well log suites

Step 1: Data description and data processing

This work was carried out using dataset made available for research and academic purpose through the Norwegian Oil & Gas Authority and license partners. The dataset consists of nineteen (19) numerical parameters acquired during drilling, including well logging data, and formation depth information composed

of 6280 rows and 19 columns. In the predictive modeling using ML algorithm the following list of log dataset are crucial, the formation porosity (NPHI), the formation bulk density (RHOB), measured in grams per cubiccentimeters. Gamma ray (GR) is the formation radioactivity content (GR), the formation true resistivity (RT), the formation photoelectric absorption factor (PEF), the borehole diameter, (CALI), the compressional ((DT), and the shear (S- wave) (DTS) sonic log. Table 1, shows a sample of recorded original data. During the data processing, the dataset was carefully checked for inconsistencies, such as negative values and outliers. It was observed that the original data contained negative values in WOB and torque which were removed. On completion of the data cleaning the data count reduced from 24403 to 21959. A total of 2,444 data points were removed from the dataset.

Table 1—Sample of dataset variables used in the ML prediction

	NPHI	RHOB	GR	RT	PEF	CALI	DT	WELL	DEPTH
0	0.371	2.356	82.746	1.323	7.126	8.648	104.605	1	2600.0
1	0.341	2.338	79.399	1.196	6.654	8.578	103.827	1	2600.1
2	0.308	2.315	74.248	1.171	6.105	8.578	102.740	1	2600.2
3	0.283	2.291	68.542	1.142	5.613	8.547	100.943	1	2600.3
4	0.272	2.269	60.314	1.107	5.281	8.523	98.473	1	2600.4

Step 2: Data Statistical Analysis

Data pre-processing and statistical analysis is a vital step in machine learning modeling and has significant effect on the performance of the algorithm. During this phase of this work, the dataset was further scrutinize by converting to the correct units, arranging the raw data into a suitable format for training predictive models. Also, exploratory and descriptive analysis of the gaps, using the original (not normalized) depth. we considered that a gap exist, if the distance between two consecutive records is larger than three times the depth step.

Table 2—Descriptive statistics of modeling variables; sonic log (DT), the gamma-ray (GR), the neutron porosity (NPHI), and the bulk density(RHOB). (a) original dataset (b) Cleaned dataset

(a) (original dataset)						
Parameters	NPHI	RHOB	GR	RT	PEF	CALI
Counts	24403	24403	24403	24403	24403	24403
Mean size	0.1699	2.4736	43.695	53.018	7.023	8.627
Std (m)	0.0991	0.1465	59.959	1630.3	1.171	0.046
Min size	0.0100	1.9806	0.8520	0.1030	4.297	8.360
25% (m)	0.0998	2.3803	10.222	1.5511	6.133	8.578
50% (m)	0.1427	2.5274	29.925	2.8340	7.348	8.625
75% (m)	0.2170	2.5783	48.708	4.5120	7.946	8.671
Max (m)	0.5932	3.0517	1124.4	62290	13.841	8.875

(b) (Cleaned dataset)						
Parameters	NPHI	RHOB	GR	RT	PEF	CALI
Counts	21595	21595	21595	21595	21595	21595
Mean size	0.1561	2.484	34.240	53.018	7.055	8.627
Std (m)	0.0825	0.137	37.733	1630.3	1.153	0.046
Min size	0.0290	2.068	1.3510	0.1030	4.503	8.360

(b) (Cleaned dataset)						
Parameters	NPHI	RHOB	GR	RT	PEF	CALI
25% (m)	0.0970	2.436	9.6600	1.5511	6.156	8.578
50% (m)	0.1360	2.535	28.4428	2.8340	7.454	8.625
75% (m)	0.1970	2.580	44.5065	4.5120	7.973	8.671
Max (m)	0.5590	3.025	309.327	62290	10.927	8.875

Step 3: Machine Learning modeling

The modeling step consist of three key steps: feature selection, hyperparameter tuning and performance assessment. In the feature extraction the key objectives to identify and remove redundant and ineffective input parameters that does not improve the performance of the algorithms. Fig.4 shows the feature selection from the modeling dataset. It can be observed Fig.4a that the variable, true resistivity (RT) does not have a defined relationship with the output variable (DT) as RT is a logarithmic function and therefore was dropped from the list of the input variables. Fig.4b shows finalized feature map of the input-output relationship. According to Belyadi and Haghighat, (2021) for any two input parameters with $\pm 90\%$ collinearity, one of the parameters will be dropped because such parameters provide the same information and hence would result in redundancy and increased dimensionality of the input data set if they are both kept.

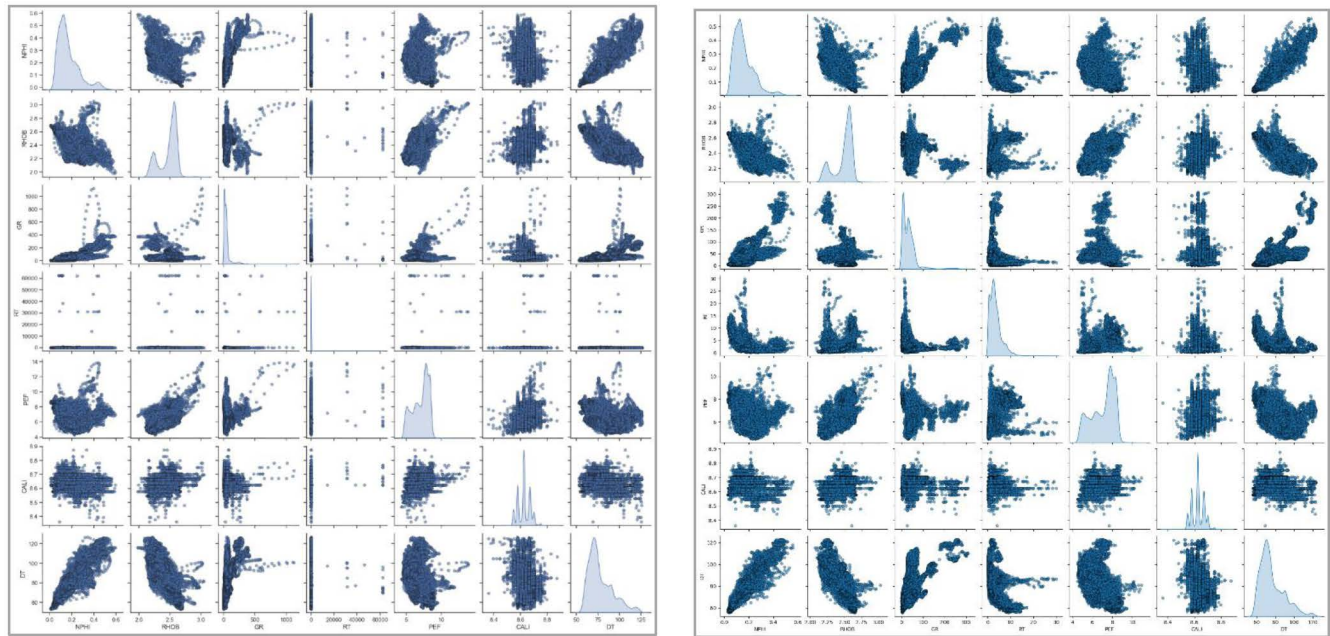


Figure 4—cross plots of selected well logs (a) before tidying the training/validation dataset (b) After outlier removal, and removal of resistivities as it is based on log function

The research employed four machine learning models: CatBoost (CB), Random Forest (RF), Support vector regressor (SVR) and Gradient Boosting, to create a model for predicting sonic (DT) values using offsets well log. Normalization and scaling methods were used to standardize the features, ensuring that no single feature would have undue influence on the model due to its scale.

Fig.5 shows the feature importance of the different log variables used in the prediction, which indicates that the formation neutron log (NPHI) and the bulk density log (RHOB) are the two most importance input variables, whilst the least effective is the borehole caliper log (CALI)

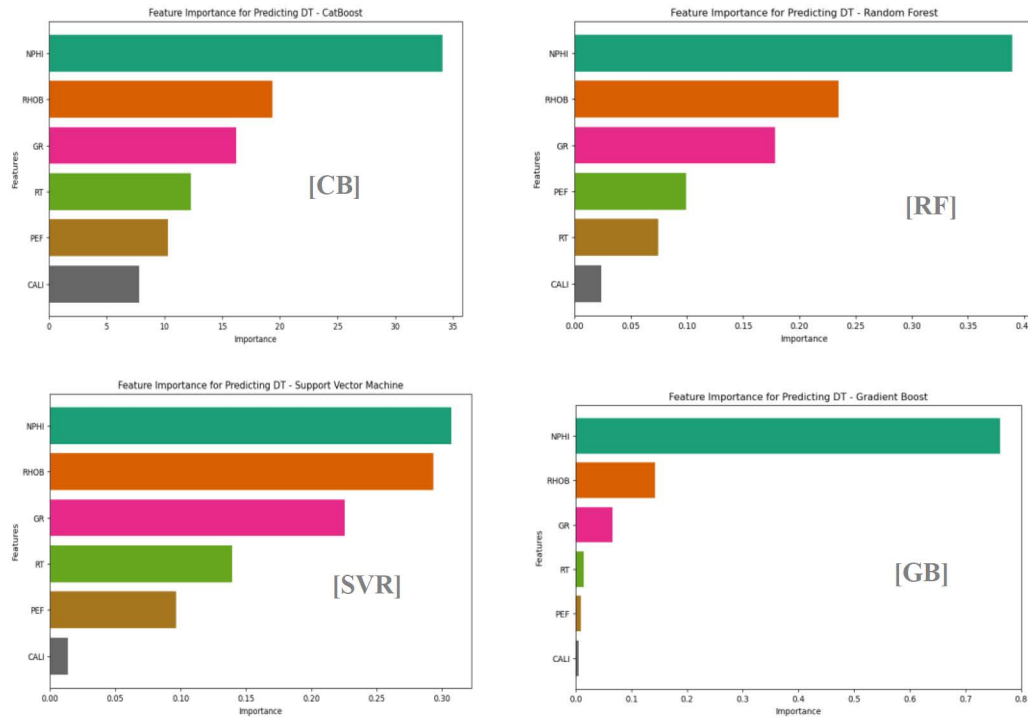


Figure 5—Feature for predicting Sonic (DT) from the different machine learning models.

Estimation of model performance.. The quality of the model was measured using different performance assessment indicators to evaluate the goodness of fit between the actual and the predicted values using the coefficient of determination (R^2) expressed as equation (5)

$$R^2 = 1 - \frac{\sum_{i=1}^n (f(xi) - yi)^2}{\sum_{i=1}^n f(xi)^2 - \sum_{i=1}^n f(yi)^2 / n} \quad (5)$$

The Mean absolute error (MAE) is a statistical measure of the relative accuracy of the model prediction. It can be calculated as the ratio of the mean of the absolute error as shown in equation (6)

$$MAE = \frac{1}{n} \sum_{i=1}^n \left[\frac{|xi - yi|}{xi} \right] \quad (6)$$

The root means square error (RMSE) is a measure of error between the actual and the predicted values. It is used as an error function for the quality evaluation of the model. It is mathematically expressed in equation (7).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (f(xi) - yi)^2} \quad (7)$$

Results and Discussion

The summary of the modeling results for sonic log prediction from the various machine learning algorithms are presented in Table 3. All the models performed excellently well with Catboost and RF emerging as the two best predictors and SVR model returned the lowest accuracy with respect to coefficient of determination (R^2).

Table 3—The Performance Assessment of four (4) ML Algorithms on Training and Test Data

Model	Training Accuracy (R ²)	Test Accuracy (R ²)	MAE(test)	RMSE(test)
SVM-R	0.930	0.92	0.038	0.05
Random Forest	0.99	0.96	0.02	0.033
CatBoost	0.99	0.97	0.02	0.032
Gradient Boost	0.96	0.95	0.025	0.04

Discussion of Results - Analysis 1

Fig. 6 (a) shows the comparison plot of the predicted well against the actual true measures DT values using the catboost predictor. It can be observed that an excellent match was observed between the actual and predicted values. Subsequently, the developed model was used to predict DT for the well-C where sonic log was not logged. Fig. (6b&c) shows the predicted sonic log (DT) using the two best predictors of catboost and random forest respectively.

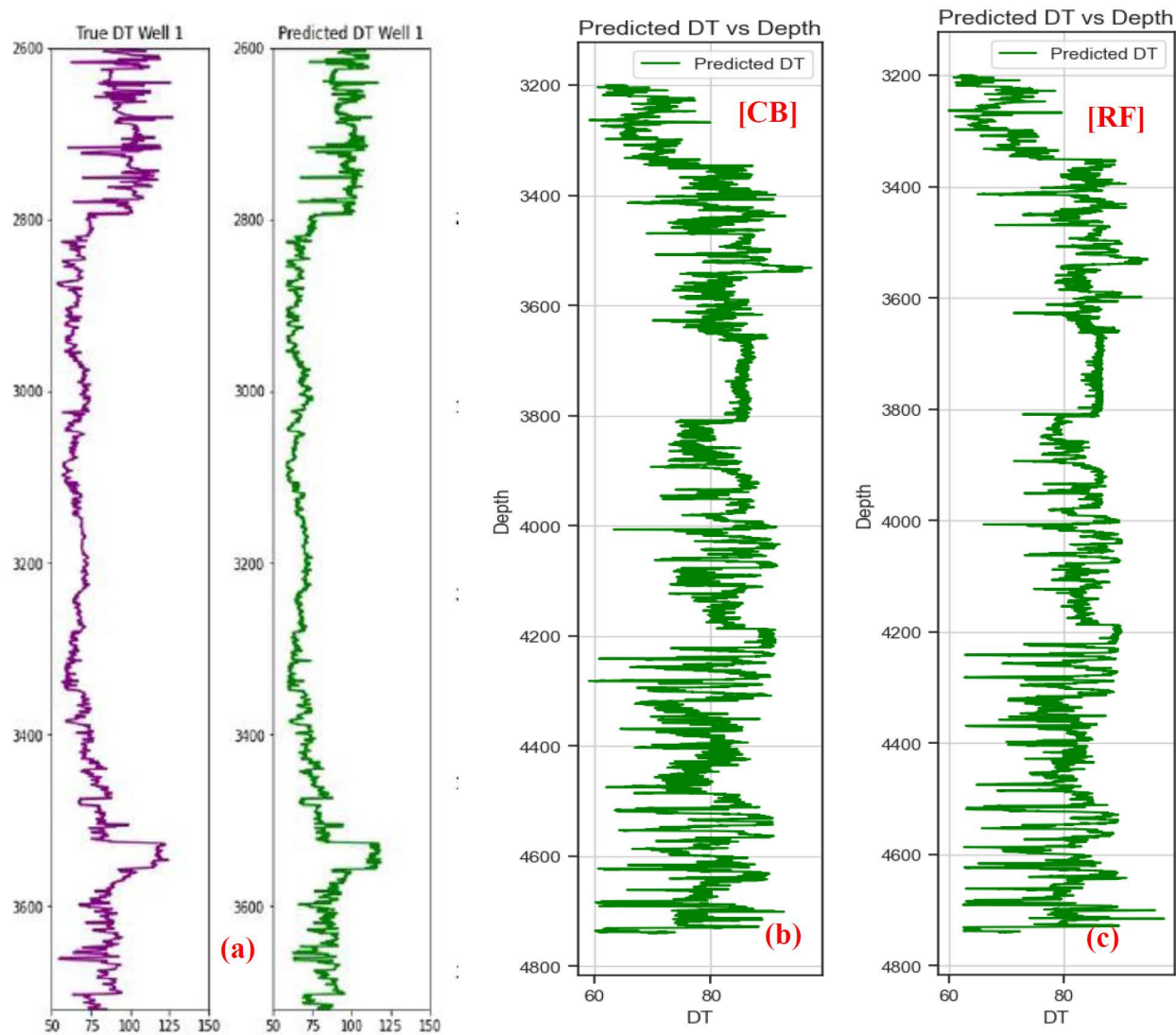


Figure 6—Plots of predicted DT (a) Actual versus Predicted for (b) Catboost prediction for unrecorded well (c) Random Forest prediction for unrecorded well

Discussion of Results - Analysis 2

Further evaluation was performed to compare the correlation of the synthetic sonic log (predicted DT) of well-c against the closest offset wells (A&B) where sonic logs were actually acquired during the drilling operation as shown in Fig.7. The comparison plot shows that predicted values are within the range when compared with the offsets. In the red box [3200-3230m] in the plot, shows that the predicted values were higher when compared to the actual values of Well-A at corresponding depths. However, the predicted DT values of well-C matched fairly with the true measure values of well-B. Which validates that these values are within the limit. At the depth of 3230 - 3260m the predicted values correlated with the values from both wells. Also on the last blue box the actual measured DT values from well A and B seems to agree reasonable very well with the predicted values of well_C

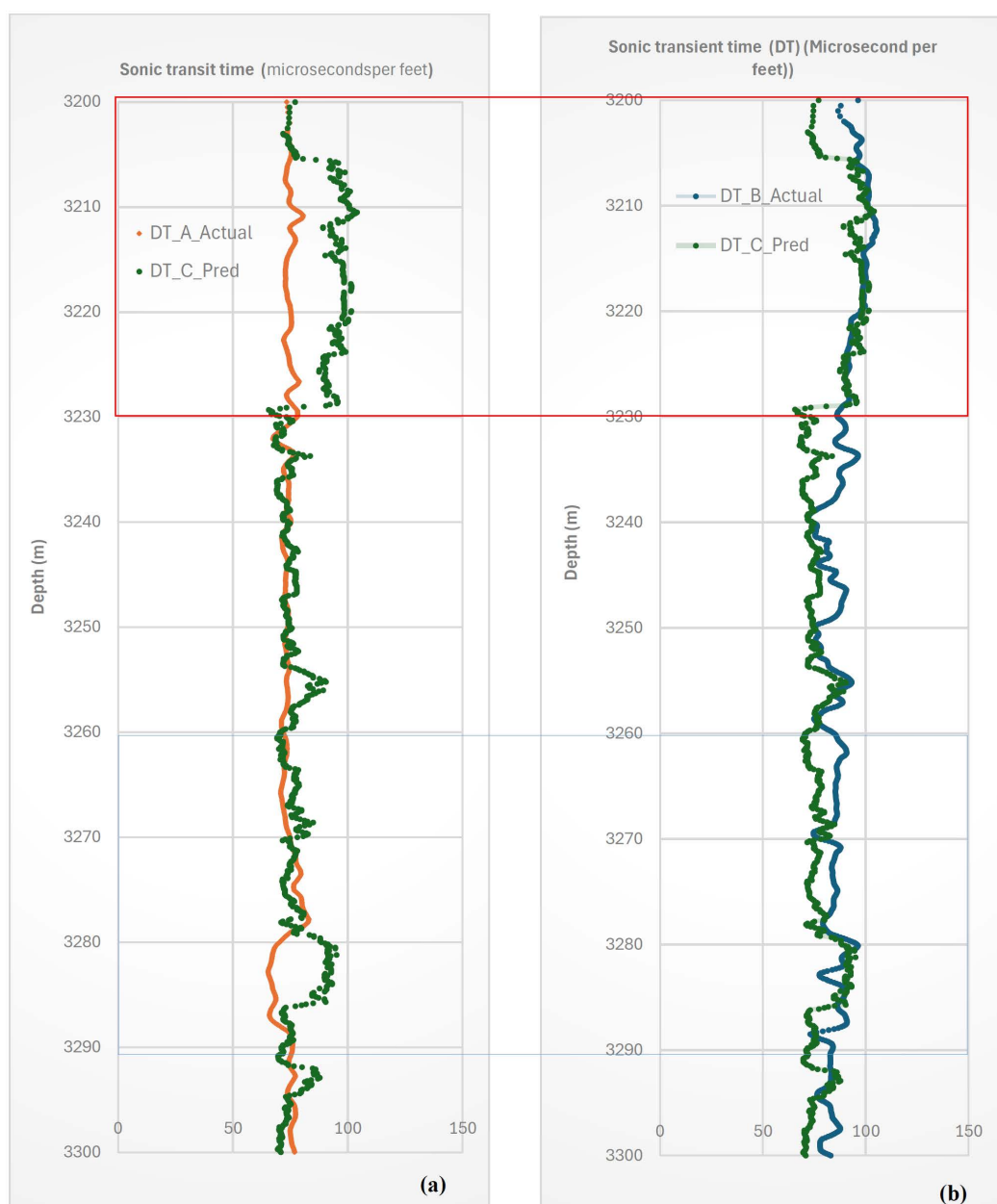


Figure 7—Comparison plots of predicted DT versus offset wells (a) Well A Actual_DT vs Well C Predicted_DT (b) Well B_Actual DT vs Well C Predicted

Conclusions

This paper used machine learning predictors; Catboost, SVR, RF, and Gradient Boost models to predict compressional sonic data from using commonly collected logs dataset such as gamma ray, neutron porosity, bulk density, and resistivity from offset wells repository taken from the Volvo offshore field in Norway. The result showed that ML predictors performed excellently, effectively predicting the compressional sonic log in well with unrecorded dataset in the logging suite. The coefficient of determination (R^2) and root mean squared error (RMSE) are the key performance metric used to measure, the predictive performance of each model. The result showed that the Catboost and the random Forest are the two best predictors and therefore selected for the actual prediction for well-C where sonic (DT) was not logged. The work further investigate the performance accuracy of ensemble model (RF) with the non-ensemble model (SVR). This study further validates the earlier works of previous investigators that reported that the ensemble algorithms are more accurate than the non-ensemble algorithms as all the ensemble algorithms used (RF, CB and GB) outperformed the non-ensemble (SVR). The novel application of machine learning in this study used in generating synthetical logs from offset well logs has the potential of reducing well delivery cost and greenhouse emissions from well construction by elimination non-critical wireline logging operation and unplanned events such as re-logging drilled section, and wiper trip runs for repeat logging operation.

Acknowledgements

The authors would like to thank the Australian University, Project Based Learning (PBL) team for their invaluable support and resources that greatly contributed to the completion of this work.

References

- Ahmadi M. A.; Chen Z. (2019) Comparison of machine learning methods for estimating permeability and porosity of oil reservoirs via petro-physical logs. *Petroleum* 2019, **5** (3), 271–284. [10.1016/j.petlm.2018.06.002](https://doi.org/10.1016/j.petlm.2018.06.002).
- Aliouane, L., Oudfeul, S., and Boudella, A. (2012) *Well-Logs Data Processing Using the Fractal Analysis and Neural Network*. IntechOpen Open Access books
- Belyadi, H., Haghighat, A., (2021) *Machine Learning Guide for Oil and Gas Using Python. A Step-by-step Breakdown with Data, Algorithms, Codes, and Applications*, Gulf Professional Publishing, an imprint of Elsevier, 2021, p. 83.
- Cranganu, C., Breaban, M. (2013) Using support vector regression to estimate sonic log distributions: a case study from the Anadarko Basin, Oklahoma, *J. Petrol. Sci. Eng.* **103** (2013) 1–13.
- Cranganu, C., Breaban, M., Mar. 2013. Using support vector regression to estimate sonic log distributions: a case study from the Anadarko Basin, Oklahoma. *J. Petrol Sci. Eng.* **103**, 1–13.
- Hamada, G., M. Elshafei M., A. (2010) Neural network prediction of porosity and permeability of heterogeneous gas sand reservoirs using NMR and conventional logs. *Nafta*. 2010 Oct 29;**61**(10):451–60.
- Helle HB, Bhatt A, Ursin B. Porosity and permeability prediction from wireline logs using artificial neural networks: a North Sea case study. *Geophysical Prospecting*. 2001; **49**(4):431–444.
- Ibrahim, A.A, Ridwan, R. L., Muhammed, M.M, Abdulaziz, R O., and Saheed, G.A (2020); Comparison of the CatBoost Classifier with other Machine Learning Methods.) *International Journal of Advanced Computer Science and Applications*, Vol. **11**, No. 11, 2020
- Johnson, E., Obot, O., Attah, K., (2023); The Use of Machine Learning in Oil Well Petrophysics and Original Oil in Place Estimation: A Systematic Literature Review Approach. *Journal of Engineering Research and Reports* 2023 July 19. DOI: [10.9734/jerr/2023/v25i6921](https://doi.org/10.9734/jerr/2023/v25i6921)
- Liu, J.S., Zhao, Y., Wang, Z., (2021) Artificial intelligence method for shear wave travel time prediction considering reservoir geological continuity, *Math. Probl Eng.* **2021** (2021) 18. Article ID 5520428.
- Majdi A, Beiki M. Evolving neural network using a genetic algorithm for predicting the deformation modulus of rock masses. *International Journal of Rock Mechanics and Mining Sciences*. 2010 Feb 1;**47**(2):246–53.
- McNamara, A., McKenzie-Brown, P., Sep. 2013. *Petroleum Exploration and Production*. <http://www.thecanadianencyclopedia.ca/en/article/petroleum-explorationand-production/>
- Oudfeul, S., and Aliouane, L., (2011b), Multifractal Analysis Revisited by the Continuous Wavelet Transform Applied in Lithofacies Segmentation from Well-Logs Data, *International Journal of Applied Physics and Mathematics*, Vol. **1**, No.1.

- Rezaee, M.R., Applegate, J.K. (1997) Shear velocity prediction from wire line logs, an example from Carnarvon Basin, NW Shelf, Australia, *SEG (Society of Exploration Geophysicists) Expanded Abstracts (16 (RP1))* (1997) 945–947
- Rui, L.L. and Ahpjo, M.J., (2018) Mind the Gap: a Well Log Data Analysis. Proceedings of the Workshop on Data Mining for Oil and Gas (DM4OG), Houston, Texas, USA, April 29th, 2017 (arXiv:1705.03451).
- Tasnia, S. (2021). *The Impact of The Iceberg Theory in Literature: A Close Reading of The Sun Also Rises and Invisible Cities*. Bachelor Thesis, Brac University.
- Timur, A. (1982), Advances in well logging, *J. Petrol. Technol.* **34** (06) (1982) 1–181.
- Tipping, M. E., (2001) Sparse Bayesian learning and the relevance vector machine, *J. Mach. Learn. 1463 Res.* **1** (2001) 211–244, <https://doi.org/10.1162/15324430152748236>.
- Wood, D. A. (2022) Optimized feature selection assists lithofacies machine learning with sparse well log data combined with calculated attributes in a gradational fluvial sequence, *Artificial Intelligence in Geosciences* **3** (2022) (2022) 132–147
- Aminzadeh, P. De Groot, F., (2006) *Neural Networks and Other Soft Computing Techniques with Applications in the Oil Industry* EAGE Publications (2006). URL <https://books.google.pt/books?id=SzFQAQAIAAJ>
- Yu, Y., Seyler, D., McCormack, M (2011) Method for estimating missing well log data Google Patents, *US Patent 8,065,086*. URL <https://www.google.com/patents/US8065086> (Nov. 2011)
- Holdaway, K. (2014); *Harness Oil and Gas Big Data with Analytics: Optimize Exploration and Production with Data Driven Models* (first ed.), Wiley Publishing (2014)
- Singh, S., Kanli, A.I, S. Sevgen, S., (2016) A general approach for porosity estimation using artificial neural network method: a case study from Kansas gas field *Studia Geophys. Geod.*, **60** (1) (Jan. 2016), pp. 130–140. URL <http://link.springer.com/10.1007/s11200-015-0820-2>
- Al-Anazi, A., Gates, I.D, (2012); A support vector machine algorithm to classify lithofacies and model permeability in heterogeneous reservoirs, *Eng. Geol.* **114** (2010) 267–277.
- Hamada GM, Elshafei MA. (2010) Neural network prediction of porosity and permeability of heterogeneous gas sand reservoirs using NMR and conventional logs. *Nafta*. 2010 Oct 29;**61**(10):451–60.
- Majdi A, Beiki M. (2010) Evolving neural network using a genetic algorithm for predicting the deformation modulus of rock masses. *International Journal of Rock Mechanics and Mining Sciences*. 2010 Feb 1;**47**(2):246–53.

Annual and seasonal mean daily discharge in natural and regulated rivers in Northern Finland: variability, trends, and links to climate teleconnections

Masoud Irannezhad ^{a,b,*}, Zahrah Abdulghafour^a and Hannu Marttila^b

^a Department of Civil Engineering, College of Engineering, Australian University, West Mishref, Safat 13015, Kuwait

^b Water, Energy and Environmental Engineering Research Unit, Faculty of Technology, University of Oulu, Oulu, Finland

*Corresponding author. E-mail: m.irannezhad@au.edu.kw

MI, 0000-0002-9634-5622

ABSTRACT

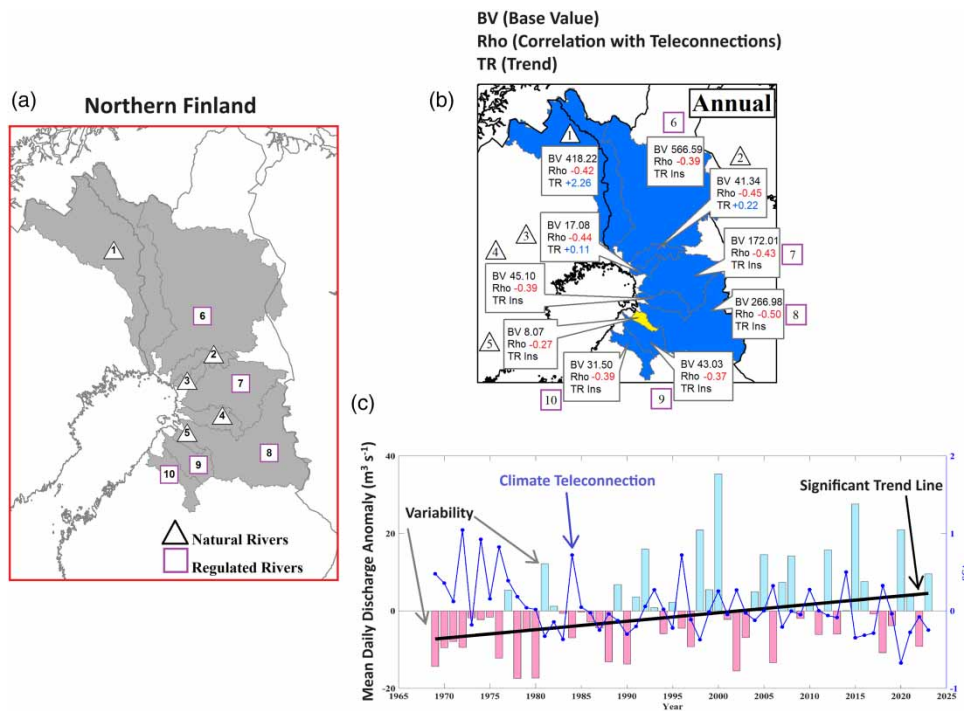
This study aimed to investigate long-term (1969–2023) variability and trends in annual mean daily discharge (AMDD) and seasonal mean daily discharge (SMDD) in 10 rivers throughout Northern Finland in connection to climate teleconnections. The lowest AMDDs were mostly recorded during the first 12 years (1969–1980) of our study period, while the highest ones were during the last 12 years (2012–2023). Significant trends in AMDD were found only in three natural rivers of Tornionjoki, Simojoki, and Kuivajoki during 1969–2023. Such variations and trends in AMDD were most significantly associated with the Scandinavia (SCA) pattern, which is also an influential climate teleconnection for annual precipitation anomalies across Northern Finland. The highest (lowest) SMDDs were experienced in spring (winter). Only increasing trends in SMDD were statistically significant ($p < 0.05$). Such substantial increases in SMDDs were detected in winter, spring, and summer (autumn) in association with the Arctic Oscillation or AO and the North Atlantic Oscillation or NAO (East Atlantic/West Russia or EA/WR). Generally speaking, recent milder and wetter climatic conditions in association with strong positive AO and NAO (negative EA/WR) phases could increase SMDD for winter, spring, and summer (autumn) seasons. Hence, both AMDD and SMDD in rivers throughout Northern Finland were primarily influenced by precipitation.

Key words: Arctic Oscillation, East Atlantic/West Russia, North Atlantic Oscillation, river discharge, Scandinavia pattern, trend analysis

HIGHLIGHTS

- The Scandinavia (SCA) pattern affects annual mean daily river discharge in Northern Finland.
- From winter to summer, daily river discharge in Northern Finland is associated with the Arctic Oscillation (OA).
- The East Atlantic/West Russia (EA/WR) influences river discharge in Northern Finland during autumn.
- Precipitation primarily controls both annual and seasonal mean daily river discharge in Northern Finland.

GRAPHICAL ABSTRACT



1. INTRODUCTION

Compared with 1850–1900, the Earth's mean global surface air temperature (SAT) was 1.1 °C warmer during 2011–2020 (IPCC 2021). Such a warming SAT was substantially higher over the lands (1.59 °C) than over the oceans (0.88 °C) (IPCC 2021). The primary cause of such increases in SAT is a rise in the atmospheric concentrations of greenhouse gas (GHG) emissions (IPCC 2021). This global warming has already influenced discharge regimes in rivers by substantially altering different hydrological cycle components, particularly precipitation, evapotranspiration, and runoff (Berghuijs *et al.* 2017; Konapala *et al.* 2020). Hence, evaluating historical river discharge time series has been one of the key study topics in international research communities focusing on climatic, hydrological, and environmental changes on local, regional, and global scales (Ashraf *et al.* 2018; Gudmundsson *et al.* 2021; Uvo *et al.* 2021).

At high latitudes, snowpack plays a key role in land surface hydrology by naturally storing water during winter and gradually releasing it into rivers in late spring and early summer as snowmelt (Jansson *et al.* 2003). Such meltwater from snowpack fundamentally controls the flow regime in northern rivers (Wilson *et al.* 2010). Hence, global warming and climate change extensively alter water resources in boreal environments by influencing snowmelt quantity and timing (Pohl *et al.* 2005). In general, warmer SAT reduces the number of cold days, the amount of snowfall, the accumulation of snowpack, and the snowmelt runoff, leading to significant changes in river discharge in cold climate regions, like Finland (Irannezhad *et al.* 2016, 2022b, 2024). Such impacts of climate warming on snow-dominated catchments, however, can be offset by more precipitation in winter, increasing snowfall, accumulating more snowpack, and delivering a higher rate of snowmelt runoff into northern rivers (Räsänen 2008). Hence, the river discharge regime at high latitudes principally depends upon changes in both regional SAT and precipitation patterns (Irannezhad *et al.* 2015b).

In general, variations in climatic conditions (particularly SAT and precipitation) across a region are influenced by large-scale atmospheric-oceanic circulation patterns, e.g. the North Atlantic Oscillation (NAO) (Glantz *et al.* 2009). The strength and natural influences of these patterns on regional climate variability are usually expressed by numeric teleconnection indices (hereafter climate teleconnections). Numerous previous studies have described the key features of such climate teleconnections (Glantz *et al.* 2009) and their effects on SAT, precipitation, and snowpack hydrological processes (SHPs) around the world (Bartolini *et al.* 2010; Hoy *et al.* 2013; Ghasemifar *et al.* 2022). In our previous studies, we mainly focused on the role of climate teleconnections on the historical variability and trends in precipitation (Irannezhad *et al.* 2014), SAT

(Irannezhad *et al.* 2015a), and SHPs (Irannezhad *et al.* 2015b), but not much on river hydrology, in Finland. Although changes in the historical river discharge regime in Finland have already been evaluated (e.g., Korhonen & Kuusisto 2010; Gohari *et al.* 2022), our knowledge about the effects of climate teleconnections on such hydrological alterations is still limited to a few studies (e.g., Uvo *et al.* 2021; Irannezhad *et al.* 2022b).

The present study aimed to investigate the influence of climate teleconnections on historical changes in the river discharge regime in Northern Finland. The specific objectives were to: (1) analyze long-term (1969–2023) variability in annual (annual mean daily discharge (AMDD)) and seasonal mean daily discharge (SMDD) in 10 rivers (both natural and regulated) in Northern Finland; (2) determine statistically significant ($p < 0.05$) trends in such times series reflecting historical discharge regimes in northern Finnish rivers, and (3) measure the correlations of these times series with different large-scale climate teleconnections. The findings can lay a foundation for forecasting future daily river discharge in these rivers based on the coming positive and negative phases of influential climate teleconnections (e.g., Wanders & Wada 2015). Such prediction of daily river discharge can play an important role in the operational processes of regulated rivers and thereby in hydropower production (e.g., Engström & Uvo 2015) in Finland. Based on Irannezhad *et al.* (2022a), hence, such an observational-based study related to river discharge regimes at high latitudes can improve our knowledge about local/regional water and energy security and thereby act toward achieving the 2030 United Nations Agenda for Sustainable Development (UN 2015).

2. MATERIAL AND METHODS

2.1. Study area

Finland is a country that extends in the south–north direction (about 1,320 km) across the boreal (or temperate) environment of northern Europe (Figure 1(a)) (de Castro *et al.* 2007). Its climate is principally controlled by both the Arctic and Atlantic Oceans, the Baltic Sea, the Scandinavian mountains, continental Eurasia, and latitudinal gradient (Käyhkö 2004). Both annual precipitation and SAT in Finland decrease from the south toward the north (Irannezhad *et al.* 2014, 2015a), but annual snow cover days increase (Irannezhad *et al.* 2016). On average, annual precipitation and mean SAT were about 601 mm (Irannezhad *et al.* 2014) and 1.7 °C (Mikkonen *et al.* 2015), respectively, on the national scale of Finland during 1911–2011. The mean annual number of days with snow cover, however, was about more than 250 in Northern Finland, but less than 130 in the southern parts (Pirinen *et al.* 2012).

The rivers in Finland are generally divided into three groups based on their flow regime (Korhonen & Kuusisto 2010). For the present study, accordingly, five natural (Torniojoki, Simojoki, Kuivajoki, Kiiminkijoki, and Temmesjoki) and five

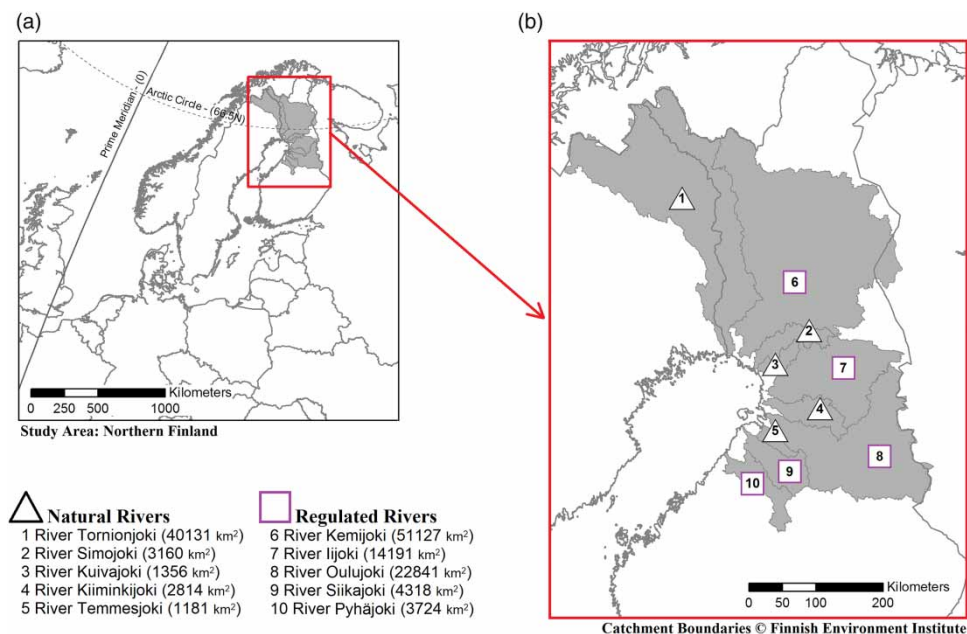


Figure 1 | The locations of (a) Northern Finland, and (b) 10 natural and regulated rivers selected for this study.

regulated (Kemijoki, Iijoki, Oulujoki, Siikajoki, and Pyhäjoki) rivers (Korhonen 2006) in Northern Finland were selected (Figure 1(b)). The River Oulujoki belongs to the first group (A), which encompasses the watershed of lakes in southern and central Finland. The Temmesjoki, Siikajoki, and Pykäjoki rivers are part of the second group (B), which comprises rivers of large sizes in Northern Finland. The third group (C), in contrast, includes medium- and small-sized river basins like Torniojoki, Simojoki, Kuivajoki, Kiiminkijoki, Kemijoki, and Iijoki rivers.

2.2. Data description

For all the natural and regulated rivers selected for this study, long-term (1968–2023) daily discharge time series, without any missing values, were collected from the Finnish Environment Institute (SYKE) (<https://www.syke.fi/en-US/Services>, accessed on 10 June 2024). Based on previous studies focusing on links between large-scale atmospheric-oceanic circulation patterns and climate variability across Finland (Irannezhad *et al.* 2014, 2015a), six climate teleconnections (Table 1) were selected. For these climate teleconnections, the monthly time series from January 1968 to December 2023 were obtained from the website of the Climate Prediction Center (CPC) at the National Oceanic and Atmospheric Administration (NOAA), USA, freely and openly available at <https://www.cpc.ncep.noaa.gov/data/teledoc/telecontents.shtml> (accessed on 10 June 2024). For this study, the calendar-based year (January–December) and climatological seasons (spring: March–May, summer: June–August, autumn: September–November, and winter: December to the following February) were considered as annual and seasonal scales, respectively. For example, the annual (winter season) time series of river discharge and climate teleconnections for 1969 referred to the period from Jan 1969 (Dec 1968) to Dec 1969 (Feb 1969).

2.3. Statistical analyses

The Mann–Kendall (MK) non-parametric test (Mann 1945) was used to detect statistically significant ($p < 0.05$, i.e. 5% significance level or 95% confidence interval) trends in AMDD and SMDD time series in selected natural and regulated rivers in Northern Finland. To quantify the magnitude of these significant trends, the Sen’s Slope method (Sen 1968) was applied. This study employed the Spearman’s rank correlation (Rho) to measure the connections of AMDD and SMDD time series with annual and seasonal climate teleconnections, respectively (Helsel & Hirsch 1992). The Rho, unlike the Pearson’s correlation coefficient (r), allocates no specific distribution functions for AMDDF and SMDDF (Helsel & Hirsch 1992). If there is a positive autocorrelation in such time series, however, the trend-free pre-whitening (TFPW) method (Yue *et al.* 2002) was used to determine significant trends, while the residual bootstrap (RB) approach (Park & Lee 2001) with 5,000 independent replications was applied for examining the standard deviation of the Rho.

3. RESULTS

3.1. Annual mean daily discharge

In Northern Finland, AMDD generally ranged from $8.07 \text{ m}^3 \text{ s}^{-1}$ in the Temmesjoki River and $565.59 \text{ m}^3 \text{ s}^{-1}$ in the Kemijoki River during 1969–2023 (Figure 2). The lowest and highest AMDDs in the Temmesjoki (Kemijoki) River were about 2.20 (394.23) and $15.93 \text{ (} 807.52 \text{)} \text{ m}^3 \text{ s}^{-1}$ recorded in 2018 (1971) and 2008 (1992), respectively (not shown). For the other rivers, however, the lowest AMDDs were mainly seen during 1976–1978: Torniojoki ($263.73 \text{ m}^3 \text{ s}^{-1}$), Simojoki ($23.86 \text{ m}^3 \text{ s}^{-1}$) (Figure 2), Kuivajoki ($8.97 \text{ m}^3 \text{ s}^{-1}$), Kiiminkijoki ($23.22 \text{ m}^3 \text{ s}^{-1}$), Iijoki ($108.70 \text{ m}^3 \text{ s}^{-1}$), Oulujoki ($184.70 \text{ m}^3 \text{ s}^{-1}$), Siikajoki ($24.24 \text{ m}^3 \text{ s}^{-1}$), and Pyhäjoki ($13.87 \text{ m}^3 \text{ s}^{-1}$). In these rivers, on the other hand, the highest AMDD (ranging from $30.72 \text{ m}^3 \text{ s}^{-1}$ in Kuivajoki to $593.42 \text{ m}^3 \text{ s}^{-1}$ in Tornionjoki) were generally measured during the last 12 years (2012–2023)

Table 1 | Summary of climate teleconnections considered in this study

No.	ID	Climate teleconnection	Source	Reference
1	AO	Arctic Oscillation	CPC	Thompson & Wallace (1998)
2	EA	East Atlantic	CPC	Barnston & Livezey (1987)
3	EA/WR	East Atlantic/West Russia	CPC	Barnston & Livezey (1987); Lim & Kim (2013)
4	NAO	North Atlantic Oscillation	CPC	Barnston & Livezey (1987)
5	POL	Polar/Eurasia pattern	CPC	Barnston & Livezey (1987)
6	SCA	Scandinavia pattern	CPC	Barnston & Livezey (1987); Bueh & Nakamura (2007)

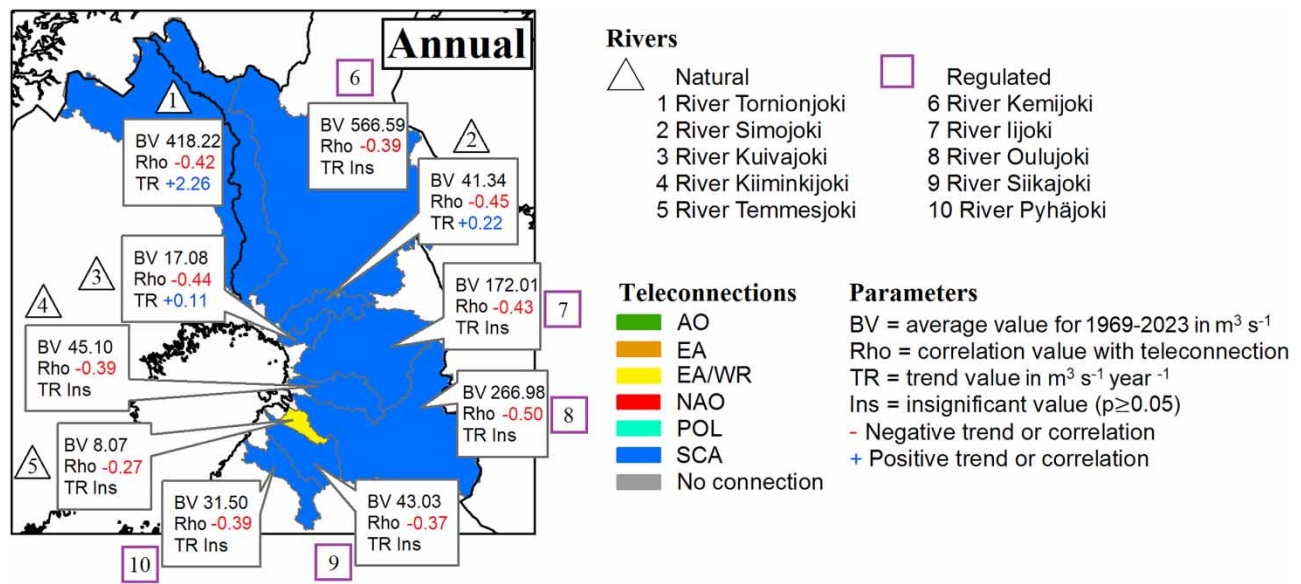


Figure 2 | Base values and trends of annual mean daily discharge (AMDD) time series for all ten natural and regulated rivers in Northern Finland and their correlations with the most influential annual climate teleconnection during 1969–2023.

of the study period (not shown). As an exception, the maximum AMDD ($76.72 \text{ m}^3 \text{ s}^{-1}$) in the Simojoki was recorded in 2000 (Figure 2).

The MK non-parametric test detected statistically significant ($p < 0.05$) trends in long-term historical AMDD only for three rivers: Tornionjoki, Simojoki, and Kuivajoki (Figure 2). These rivers are natural (unregulated) and showed increasing trends in AMDD during 1969–2023. The rate of such increases was about 2.26 , 0.22 , and $0.11 \text{ (m}^3 \text{ s}^{-1} \text{ year}^{-1}\text{)}$ for Tornionjoki, Simojoki, and Kuivajoki (Figure 2), respectively. The interannual variability and trend in AMDD in the Simojoki River during 1969–2023 are illustrated in Figure 3. No significant trends, however, were found in AMDD in the regulated rivers selected by this study across Northern Finland (Figure 2).

In general, the SCA was the most influential climate teleconnection for interannual variability and trends in AMDD in Northern Finland's rivers during 1969–2023 (Figure 2). Statistically significant ($p < 0.05$) correlations (Rho) of this climate teleconnection (SCA) with AMDD in 90% of selected rivers ranged between -0.50 and -0.27 (Figure 2). Such a negative relationship is shown in Figure 3 for the Simojoki River ($\text{Rho} = -0.45$, $p < 0.05$). Beside the SCA, the East Atlantic (EA)/WR was also an influential climate teleconnection for variability in AMDD in 80% of rivers in Northern Finland during 1969–2023, with Rho ranging from -0.39 to -0.27 (Figure 4). For the three rivers of Simojoki, Kuivajoki, and Kiiminkijoki, AMDD time series were similarly correlated with the EA ($\text{Rho} = 0.26$ – 0.28) (Figure 4). However, all Arctic oscillation (AO), NAO, and POL showed no statistically significant relationships with historical AMDD in Northern Finland rivers selected for this study (Figure 4).

3.2. Seasonal mean daily discharge

In general, the maximum and minimum base values of SMDDF in northern Finnish rivers were measured for spring and winter, respectively (Figure 5). Exceptionally, Tornionjoki (Oulujoki) as a natural (regulated) river experienced the highest SMDD base value in the summer (winter) season (Figure 5). The base values of SMDD for spring ranged from $17.10 \text{ m}^3 \text{ s}^{-1}$ in the Temmesjoki River to $763.01 \text{ m}^3 \text{ s}^{-1}$ in the Kemijoki River (Figure 5(a)). For summer (autumn), such values were between 5.29 (5.56) $\text{m}^3 \text{ s}^{-1}$ in the Temmesjoki River and 701.78 (496.96) $\text{m}^3 \text{ s}^{-1}$ in the Tornionjoki (Kemijoki) River, respectively (Figure 5(b) and 5(c)). Similarly, the lowest (highest) SMDD base value for winter was found in the Temmesjoki (Kemijoki) River (Figure 5(d)).

During 1969–2023, all statistically significant ($p < 0.05$) trends found in SMDD in both natural and regulated rivers in Northern Finland for spring, summer, autumn, and winter were positive or increasing (Figure 5). For spring, such increases were at the rates of 3.55 , 1.62 , and $0.30 \text{ (m}^3 \text{ s}^{-1} \text{ year}^{-1}\text{)}$ for the Tornionjoki, Oulujoki, and Pyhäjoki rivers, respectively

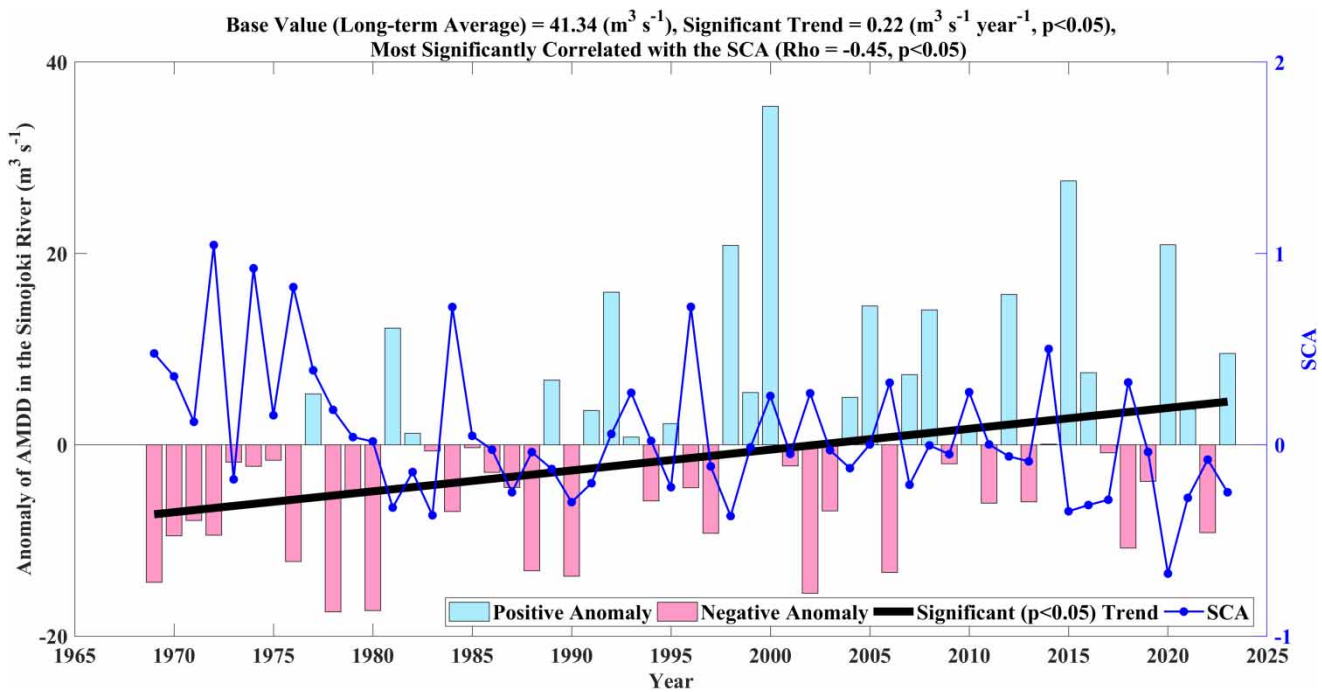


Figure 3 | Anomalies with significant trend line ($p < 0.05$) and the most influential annual climate teleconnection for annual mean daily discharge (AMDD) in the Sijojoki River in Northern Finland during 1969–2023.

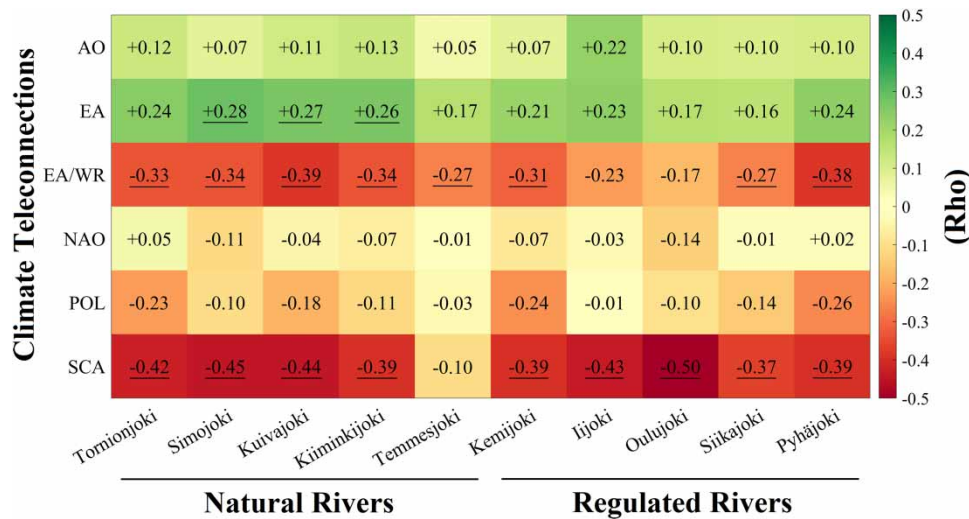


Figure 4 | The Spearman's rank correlations (Rho) of annual climate teleconnections with annual mean daily discharge (AMDD) in all 10 selected natural and regulated rivers across Northern Finland during 1969–2023. The underlined values show statistically significant ($p < 0.05$) correlations.

(Figure 5(a)). The first river (Tornionjoki) also experienced increasing trends in SMDD time series for autumn ($2.56 \text{ m}^3 \text{ s}^{-1} \text{ year}^{-1}$) and winter ($1.01 \text{ m}^3 \text{ s}^{-1} \text{ year}^{-1}$) (Figure 5(c) and 5(d)). For these two seasons (autumn and winter), substantial increases (ranging between 0.21 and $2.56 \text{ m}^3 \text{ s}^{-1} \text{ year}^{-1}$) were detected in SMDD in Sijojoki, Kuivajoki, Kiiminkijoki, Kemijoki, and Iijoki (Figure 5(c) and 5(d)). Three of these rivers (Kemijoki, Kuivajoki, and Iijoki), moreover, showed statistically significant trends in SMDD time series during the summer season (Figure 5(b)). For both Temmesjoki and Siikajoki, however, no clear changes were found in SMDD during any of the four seasons over time (Figure 5).

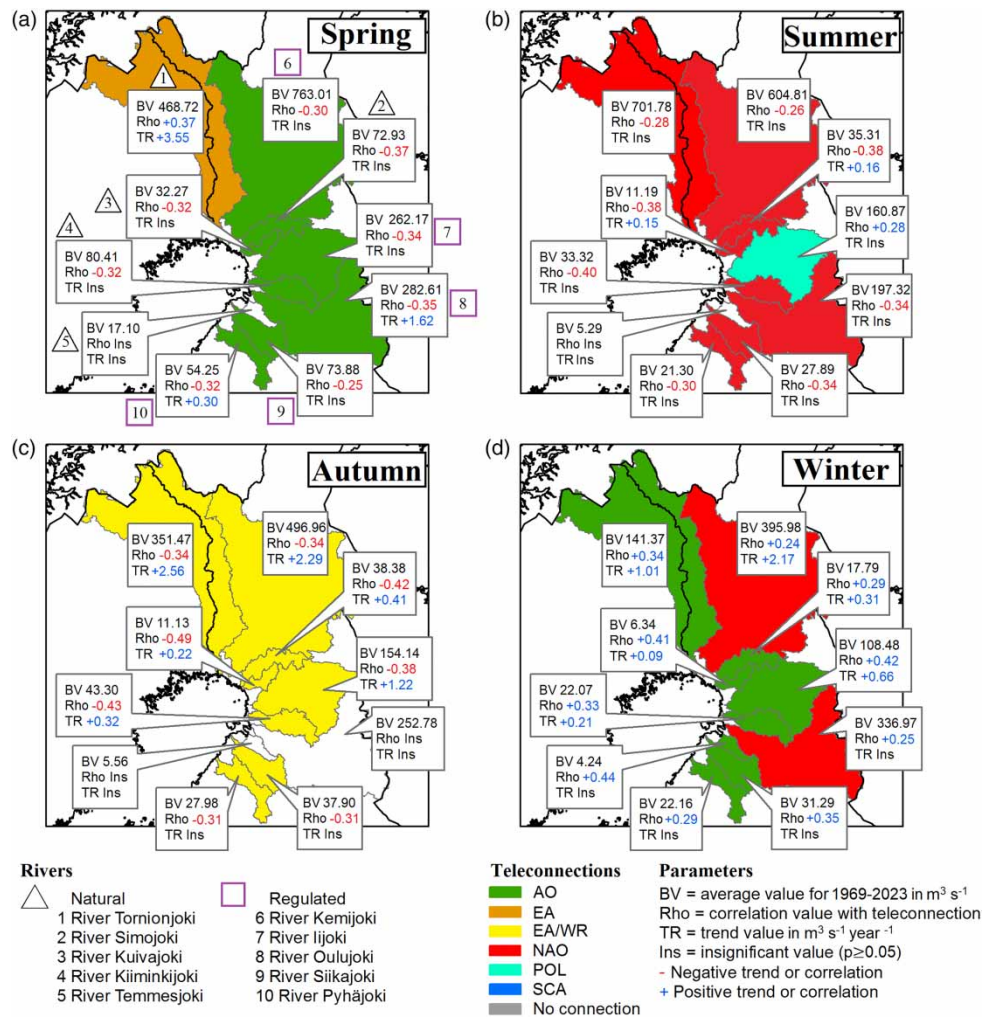


Figure 5 | Base values and trends of seasonal mean daily discharge (SMDD) in all 10 selected natural and regulated rivers in Northern Finland and their correlations with the most influential seasonal climate teleconnection during 1969–2023 for the (a) spring, (b) summer, (c) autumn, and (d) winter seasons.

In Northern Finland, SMDD times series for spring, summer, and autumn showed the strongest correlations with the SCA ($\text{Rho} = -0.37$ to -0.25), NAO ($\text{Rho} = -0.40$ to -0.26), and EA/WR ($\text{Rho} = -0.79$ to -0.31), respectively (Figure 6(a)–6(c)). The NAO and EA/WR were also the most influential climate teleconnections for wintertime SMDD variability in northern Finnish rivers, with $\text{Rho} = 0.24$ to 0.44 (Figure 6(d)). Besides these three climate teleconnections, the EA showed statistically significant correlations with SMDD in Northern Finland's rivers for spring and autumn, with $\text{Rho} = 0.24$ to 0.37 (Figure 6(a) and 6(c)). For the Temmesjoki River, however, there was no clear relationship between the climate teleconnections and SMDD during spring, summer, and autumn (Figure 6(a)–6(c)).

4. DISCUSSION

4.1. River discharge regime in Northern Finland

In general, both climatic and human impacts play critical roles in significant changes in historical river discharge regimes around the world. Human activities such as land cover-land use changes, bog drainage, and regulations have already influenced discharge in some river basins (e.g., *Irannezhad et al. 2018*). Changes in climatic conditions have also altered different characteristics (in terms of magnitude and timing) of river discharge in different parts of our planet (e.g., *Minaii*

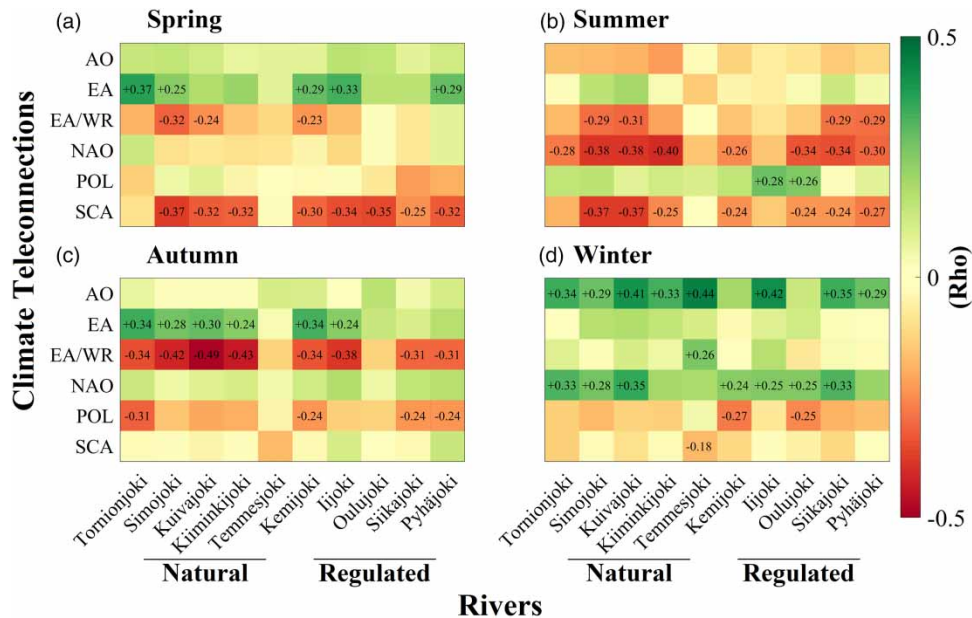


Figure 6 | The Spearman's rank correlations (Rho) of seasonal climate teleconnections with seasonal mean daily discharge (SMDD) in all 10 selected natural and regulated rivers across Northern Finland during 1969–2023 for the (a) spring, (b) summer, (c) autumn, and (d) winter seasons. The given values are statistically significant ($p < 0.05$) correlations.

& Irannezhad 2018). At high latitudes, accordingly, significant alterations in river discharge are one of the key hydrological responses to global warming, climate change, and human activities (Korhonen & Kuusisto 2010; Blöschl *et al.* 2019).

The present study found statistically significant (all increasing) trends in historical (1969–2023) AMDD in only three rivers of Tornionjoki, Simojoki, and Kuivajoki. All these natural rivers are located in Region C of the Finnish Rivers System, with abundant annual flow because there are not as many lakes as the water reservoirs (Korhonen & Kuusisto 2010). Such increases in AMDD in these rivers can be explained by more annual precipitation (Irannezhad *et al.* 2014), warmer annual mean SAT (Irannezhad *et al.* 2015a), and consequently a higher amount of rainfall across their basins. Besides such climatic factors, different human activities, like extensive drainage operations mainly in peatland forests, changed land cover in the basin of these rivers and thereby modified their AMDD over time (Meriö *et al.* 2019). Similar to our findings, on the other hand, previous studies also determined no significant trends in mean annual flow in regulated rivers in Finland during 1912–2004 (Korhonen & Kuusisto 2010).

For winter, this study found statistically significant increasing trends in SMDD in both natural and regulated rivers in Northern Finland during 1963–2010. Korhonen & Kuusisto (2010) also reported increases in wintertime river discharge in Northern Finland in recent decades. Similar to our findings, they concluded that the main cause of such increases, particularly for natural rivers, was more rainfall due to the milder and wetter climatic conditions during winter in recent decades. For the regulated rivers in Northern Finland, however, the other reason behind such SMDD increases in winter was the higher rates of water release from the hydropower dams during winter match the cold season energy needs and create enough storage capacity for snowmelt approaching the end of winter or the early spring (Korhonen & Kuusisto 2010).

For spring, SMDD increased in only one natural river (Tornionjoki) and two regulated rivers (Oulujoki and Pyhäjoki) across Northern Finland during 1969–2023. Korhonen & Kuusisto (2010) also found a significant increasing trend in historical springtime river discharge in both Tornionjoki and Oulujoki. This could be related to warmer springtime SAT resulting in a rapid snowpack ablation accelerated by more frequent rain on snow events (Uvo *et al.* 2021). Hence, toward the end of the spring season, snowmelt declined and rainfall runoff became the dominant contributor to river discharge in such snow-dominant catchments (Uvo *et al.* 2021). However, increases in springtime SMDD in regulated rivers can also be explained by releasing water for securing its supply and power generation at the end of spring and in the early summer, when droughts are common in Northern Finland due to less and early springtime snowmelt runoff (Okkonen & Kløve 2010).

Similar to Korhonen & Kuusisto (2010), the present study found considerable increases in summertime river discharge in two natural rivers (Simojoki and Kuivajoki) in Northern Finland. Such increases might be related to more summer

precipitation across this part of the country (Irannezhad *et al.* 2014) and higher rates of drainage from both forest and peat-land areas (Korhonen & Kuusisto 2010). For autumn, the present study found only significant increases in SMDD in both natural (Tornionjoki, Simojoki, Kuivajoki, and Kiiminkijoki) and regulated rivers (Kemijoki and Iijoki) during 1969–2023. In the era of global warming, higher SAT during autumn can result in slower and later soil frost processes before winter in Northern Finland, thereby accelerating infiltration, enhancing deeper flow paths, mobilizing subsurface water, and consequently increasing river discharge (Evans *et al.* 2020). More rainfall on snow events during the late autumn might also increase river discharge in northern Finnish rivers (Rawlins *et al.* 2009; Gohari *et al.* 2022).

4.2. The role of climate teleconnections

In general, the SCA was the most significant climate teleconnection controlling variability and trends in AMDD in Northern Finland's rivers during 1969–2023. Similarly, Uvo *et al.* (2021) concluded that discharge regimes in river basins at high latitudes in Northern Europe were negatively associated with variations in the SCA during 1960–2010. According to previous studies, the SCA was also one of the climate teleconnections negatively influencing precipitation (mainly rainfall) (Irannezhad *et al.* 2017) variability across Northern Finland (Irannezhad *et al.* 2014). Similar to Korhonen (2006), this confirmed that AMDD in rivers across Northern Finland is mainly influenced by precipitation variability rather than changes in snowmelt under global warming. The primary circulation center of this climate teleconnection (SCA) is located across the Scandinavian Peninsula and the Siberian segment of the Arctic Ocean (Barnston & Livezey 1987). The other two weaker centers of opposite anomalies sign are located across Western Europe and eastern Russia/western Mongolia (Bueh & Nakamura 2007). The SCA negative (positive) phase expresses low (high) pressure anomalies across the Norwegian Sea, Greenland, and Scandinavian region, bringing wetter (drier) airflow toward Finland (Bueh & Nakamura 2007). However, the positive phase of SCA may sometimes describe the main blocking anticyclones across Scandinavia and Western Russia. Such a natural sign of SCA was clearly reflected by the significant negative relationships found by this study between AMDD in Northern Finland's rivers and the SCA. In fact, the positive (negative) values of SCA were associated with lower (high) AMDD than normal in Northern Finland's rivers, particularly during the first (last) 12 years of our study period from 1969 to 1980 (2012–2023).

For winter, spring, and summer, the AO and NAO were generally the most significant teleconnection positively influencing SMDD in rivers across Northern Finland during 1969–2023. Similarly, Uvo *et al.* (2021) concluded that streamflows in snow-dominated catchments at high latitudes in northern Europe were positively associated with the AO during 1960–2010. This climate teleconnection also influenced peak spring flood discharge in rivers across Northern Finland during 1967–2011 (Irannezhad *et al.* 2022b). The AO indicates the power of the circumpolar vortex, while the NAO describes the intensity of west circulation from the North Atlantic to the Atlantic European section (Thompson & Wallace 1998). In general, hence, the NAO is considered a main component of the AO (Serreze *et al.* 2000). Their positive and negative phases naturally correspond to strong and weak westerly circulations, transporting mild maritime and cold airflows over Northern Europe, respectively, during the winter season (Gormsen *et al.* 2005; Jaagus 2006). In recent decades, the AO (NAO) power increased by 0.26 (0.20) decade⁻¹ (Wang *et al.* 2005), resulting in milder and wetter winters throughout Northern Finland (Irannezhad *et al.* 2014, 2015a). This could significantly warm SAT, thereby increasing rainfall (Irannezhad *et al.* 2016), and consequently raising the rate of discharge in rivers across Northern Finland during the winter, spring, and summer seasons in 1969–2023.

In Northern Finnish rivers, SMDD time series for autumn were negatively associated with the EA/WR anomalies. Previous studies also reported statistically significant negative correlations between the EA/WR and SMDD in rivers at high latitudes in Northern Europe during the spring, summer, and autumn seasons (Uvo *et al.* 2021; Irannezhad *et al.* 2022b). The EA/WR describes the meridional circulation for Finland that naturally weakens with the strengthening of the westerly airflows. It is a zonally oriented climate teleconnection consisting of (i) two anomaly centers located across the Caspian Sea and Western Europe in winter, and (ii) three anomaly centers across the coast of Portugal, north-west Europe, and west-north-west Russia during spring–autumn. In general, the negative (positive) EA/WR phase is associated with the anomalous southerly and southeasterly (northerly and northwesterly) airflows, bringing wetter (drier) and milder (colder) climatic conditions across Northern Europe, including Finland (Lim & Kim 2013; Irannezhad *et al.* 2014, 2015a). In rivers across Northern Finland, hence, significant increases in SMDD time series for autumn can be explained by their negative relationships with the EA/WR that similarly generate precipitation runoff rates in Northern Europe.

Interestingly, we did not notice major differences in the effects of climate teleconnections on annual and seasonal mean discharge between regulated and unregulated river systems. The regulated river systems selected by this study are runoff-

river types (Ashraf *et al.* 2016) with limited storage capacity in the mainstream, while the main storages in the upper catchments are natural or artificial (only for the Kemijoki River) lakes that play an important role in the regulation processes (Ashraf *et al.* 2016). Hence, the main storage capacity in these regulated river systems is lower than in many other hydro-power rivers worldwide (Marttila *et al.* 2024). Such regulations influence river discharge primarily within day and week scales (Ashraf *et al.* 2018; Virk *et al.* 2024), shift peak spring flood discharge timing (Irannezhad *et al.* 2022b), and increase wintertime base flow due to higher energy need during this season (Ashraf *et al.* 2018; Virk *et al.* 2024). However, these effects were not seen that strongly in our analyses focusing on long-term variability and trends in annual and seasonal mean daily discharge time series and their connections to teleconnections.

5. CONCLUSIONS

The present study analyzed long-term (1969–2023) historical variations and trends in river discharge throughout Northern Finland and their relationships to large-scale climate teleconnections. The major findings were as follows:

- In both natural and regulated rivers in Northern Finland, the lowest and highest AMDDF were generally recorded in the first (1969–1980) and last (2012–2023) 12 years of our study period, respectively. Statistically significant trends in AMDD were found only for three natural rivers of Tornionjoki, Simojoki, and Kuivajoki during 1969–2023. Such historical variations and changes in AMDD time series were most significantly controlled by the SCA, which is also one of the influential climate teleconnections for interannual precipitation variability across Northern Finland. Although snowpack hydrological processes have already been affected by global warming, our findings might prove that precipitation variability more than snowmelt controls AMDD in rivers throughout Northern Finland under climate change.
- The highest and lowest SMDD in rivers across Northern Finland were generally experienced in spring and winter, respectively. For these rivers, only increasing trends in SMDD were statistically significant ($p < 0.05$). These substantial increases during winter, spring, and summer were generally associated with the stronger AO and NAO positive phases in recent decades, bringing more precipitation, milder SAT, and consequently more rainfall across Northern Finland. For autumn, SMDD increased in those rivers with statistically significant correlations with the EA/WR, the climate teleconnection negatively controlling both precipitation and SAT over Finland. Generally speaking, the recent stronger negative phases of this climate teleconnection (EA/WR) modified different hydrological processes (mainly infiltration) in Northern Finland by not only increasing precipitation in autumn but also postponing the winter season. In conclusion, hence, SMDD in rivers in Northern Finland are generally controlled by the climate teleconnections primarily affecting seasonal precipitation across this country: the AO and NAO for winter, spring, and summer, while the EA/WR for autumn.

ACKNOWLEDGEMENTS

The authors are grateful to the Finnish Environment Institute (SYKE) for monitoring and recording historical daily river discharge in Finland. They would also acknowledge the Climate Prediction Center (CPC) at the National Oceanic and Atmospheric Administration (NOAA) of the United States for making available online the standardized monthly values of climate teleconnections used in this study.

FUNDING

This study was funded by the Sakari Alhopuro Foundation (Grants 20220247 and 20230218), and Maa- ja vesitekniiikan tuky r.y. (Grants 44008 and 45599).

DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

- Ashraf, F. B., Haghighi, A. T., Marttila, H. & Kløve, B. 2016 Assessing impacts of climate change and river regulation on flow regimes in cold climate: A study of a pristine and a regulated river in the sub-arctic setting of Northern Europe. *Journal of Hydrology* **542**, 410–422. <https://doi.org/https://doi.org/10.1016/j.jhydrol.2016.09.016>.
- Ashraf, F. B., Haghighi, A. T., Riml, J., Alfredsen, K., Koskela, J. J., Kløve, B. & Marttila, H. 2018 Changes in short term river flow regulation and hydropeaking in Nordic rivers. *Scientific Reports* **8** (1), 17232. <https://doi.org/10.1038/s41598-018-35406-3>.
- Barnston, A. G. & Livezey, R. E. 1987 Classification, seasonality and persistence of low-frequency atmospheric circulation patterns. *Monthly Weather Review* [https://doi.org/10.1175/1520-0493\(1987\)115<1083:CSAPOL>2.0.CO;2](https://doi.org/10.1175/1520-0493(1987)115<1083:CSAPOL>2.0.CO;2).
- Bartolini, E., Claps, P. & D'Odorico, P. 2010 Connecting European snow cover variability with large scale atmospheric patterns. *Advances in Geosciences* **26**, 93–97. <https://doi.org/10.5194/adgeo-26-93-2010>.
- Berghuijs, W. R., Larsen, J. R., van Emmerik, T. H. M. & Woods, R. A. 2017 A global assessment of runoff sensitivity to changes in precipitation, potential evaporation, and other factors. *Water Resources Research* <https://doi.org/10.1002/2017WR021593>.
- Blöschl, G., Bierkens, M. F. P., Chambel, A., Cudennec, C., Destouni, G., Fiori, A., Kirchner, J. W., McDonnell, J. J., Savenije, H. H. G., Sivapalan, M., Stumpff, C., Toth, E., Volpi, E., Carr, G., Lupton, C., Salinas, J., Széles, B., Viglione, A., Aksoy, H., Allen, S. T., Amin, A., Andréassian, V., Arheimer, B., Aryal, S. K., Baker, V., Bardsley, E., Barendrecht, M. H., Bartosova, A., Batelaan, O., Berghuijs, W. R., Beven, K., Blume, T., Bogaard, T., de Amorim P. B., Böttcher, M. E., Boulet, G., Breinl, K., Brilly, M., Brocca, L., Buytaert, W., Castellarin, A., Castelletti, A., Chen, X., Chen, Y., Chen, Y., Chiffard, P., Claps, P., Clark, M. P., Collins, A. L., Croke, B., Dathe, A., David, P. C., de Barros, F. P. J., de Rooij, G., Di Baldassarre, G., Driscoll, J. M., Duethmann, D., Dwivedi, R., Eris, E., Farmer, W. H., Feccabrino, J., Ferguson, G., Ferrari, E., Ferraris, S., Fersch, B., Finger, D., Foglia, L., Fowler, K., Gartsman, B., Gascoin, S., Gaume, E., Gelfan, A., Geris, J., Gharari, S., Gleeson, T., Glendell, M., Gonzalez Bevacqua, A., González-Dugo, M. P., Grimaldi, S., Gupta, A. B., Guse, B., Han, D., Hannah, D., Harpold, A., Haun, S., Heal, K., Helfricht, K., Herrnegger, M., Hipsey, M., Hlaváčiková, H., Hohmann, C., Holko, L., Hopkinson, C., Hrachowitz, M., Illangasekare, T. H., Inam, A., Innocente, C., Istanbuluoglu, E., Jarihani, B., Kalantari, Z., Kalvans, A., Khanal, S., Khatami, S., Kiesel, J., Kirkby, M., Knoben, W., Kochanek, K., Kohnová, S., Kolehckina, A., Krause, S., Kremer, D., Kreibich, H., Kunstmann, H., Lange, H., Liberato, M. L. R., Lindquist, E., Link, T., Liu, J., Loucks, D. P., Luce, C., Mahé, G., Makarieva, O., Malard, J., Mashtayeva, S., Maskey, S., Mas-Pla, J., Mavrova-Guirguinova, M., Mazzoleni, M., Mernild, S., Misstear, B. D., Montanari, A., Müller-Thomy, H., Nabizadeh, A., Nardi, F., Neale, C., Nesterova, N., Nurtaev, B., Odongo, V. O., Panda, S., Pande, S., Pang, Z., Papacharalampous, G., Perrin, C., Pfister, L., Pimentel, R., Polo, M. J., Post, D., Prieto Sierra, C., Ramos, M.-H., Renner, M., Reynolds, J. E., Ridolfi, E., Rigon, R., Riva, M., Robertson, D. E., Rosso, R., Roy, T., Sá, J. H. M., Salvadori, G., Sandells, M., Schaeffli, B., Schumann, A., Scolobig, A., Seibert, J., Servat, E., Shafiei, M., Sharma, A., Sidibe, M., Sidle, R. C., Skaugen, T., Smith, H., Spiessl, S. M., Stein, L., Steinsland, I., Strasser, U., Su, B., Szolgay, J., Tarboton, D., Tauro, F., Thirel, G., Tian, F., Tong, R., Tussupova, K., Tyralis, H., Uijlenhoet, R., van Beek, R., van der Ent, R. J., van der Ploeg, M., Van Loon, A. F., van Meerveld, I., van Nooijen, R., van Oel, P. R., Vidal, J.-P., von Freyberg, J., Vorogushyn, S., Wachniew, P., Wade, A. J., Ward, P., Westerberg, I. K., White, C., Wood, E. F., Woods, R., Xu, Z., Yilmaz, K. K. & Zhang, Y. 2019 Twenty-three unsolved problems in hydrology (UPH) – a community perspective. *Hydrological Sciences Journal* **64** (10), 1141–1158. <https://doi.org/10.1080/02626667.2019.1620507>.
- Bueh, C. & Nakamura, H. 2007 Scandinavian pattern and its climatic impact. *Quarterly Journal of the Royal Meteorological Society* <https://doi.org/10.1002/qj.173>.
- de Castro, M., Gallardo, C., Jylha, K. & Tuomenvirta, H. 2007 The use of a climate-type classification for assessing climate change effects in Europe from an ensemble of nine regional climate models. *Climatic Change* **81** (1), 329–341. <https://doi.org/10.1007/s10584-006-9224-1>.
- Engström, J. & Uvo, C. 2015 Effect of northern hemisphere teleconnections on the hydropower production in southern Sweden. *Journal of Water Resources Planning and Management* **142**, 5015008. [https://doi.org/10.1061/\(ASCE\)WR.1943-5452.0000595](https://doi.org/10.1061/(ASCE)WR.1943-5452.0000595).
- Evans, S. G., Yokeley, B., Stephens, C. & Brewer, B. 2020 Potential mechanistic causes of increased baseflow across northern Eurasia catchments underlain by permafrost. *Hydrological Processes* **34** (11), 2676–2690. <https://doi.org/https://doi.org/10.1002/hyp.13759>.
- Ghasemifar, E., Irannezhad, M., Minaei, F. & Minaei, M. 2022 The role of ENSO in atmospheric water vapor variability during cold months over Iran. *Theoretical and Applied Climatology* **148**, 795–817.
- Glantz, M. H., Katz, R. & Nicholls, N. 2009 *Teleconnections Linking Worldwide Climate Anomalies : Scientific Basis and Societal Impact* Cambridge University Press.
- Gohari, A., Shahrood, A. J., Ghadimi, S., Alborz, M., Patro, E. R., Kløve, B. & Haghighi, A. T. 2022 A century of variations in extreme flow across Finnish rivers. *Environmental Research Letters* **17** (12), 124027. IOP Publishing. <https://doi.org/10.1088/1748-9326/aca554>.
- Gormsen, A. K., Hense, A., Toldam-Andersen, T. B. & Braun, P. 2005 Large-scale climate variability and its effects on mean temperature and flowering time of *Prunus* and *Betula* in Denmark. *Theoretical and Applied Climatology* **82** (1), 41–50. <https://doi.org/10.1007/s00704-005-0122-7>.
- Gudmundsson, L., Boulange, J., Do, H. X., Gosling, S. N., Grillakis, M. G., Koutroulis, A. G., Leonard, M., Liu, J., Schmied, H. M., Papadimitriou, L., Pokhrel, Y., Seneviratne, S. I., Satoh, Y., Thiery, W., Westra, S., Zhang, X. & Zhao, F. 2021 Globally observed trends in mean and extreme river flow attributed to climate change. *Science* **371** (6534), 1159–1162. <https://doi.org/10.1126/science.aba3996>.
- Helsel, D. R. & Hirsch, R. M. 1992 *Statistical methods in water resources*. *Statistical Methods in Water Resources* <https://doi.org/10.2307/1269385>.
- Hoy, A., Sepp, M. & Matschullat, J. 2013 Large-scale atmospheric circulation forms and their impact on air temperature in Europe and northern Asia. *Theoretical and Applied Climatology* **113** (3), 643–658. <https://doi.org/10.1007/s00704-012-0813-9>.

- IPCC. 2021 *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu & B. Zhou, eds). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Irannezhad, M., Marttila, H. & Kløve, B. 2014 Long-term variations and trends in precipitation in Finland. *International Journal of Climatology* <https://doi.org/10.1002/joc.3902>.
- Irannezhad, M., Chen, D. & Kløve, B. 2015a Interannual variations and trends in surface air temperature in Finland in relation to atmospheric circulation patterns, 1961–2011. *International Journal of Climatology* **35** (10), 3078–3092. <https://doi.org/https://doi.org/10.1002/joc.4193>.
- Irannezhad, M., Ronkanen, A.-K. & Kløve, B. 2015b Effects of climate variability and change on snowpack hydrological processes in Finland. *Cold Regions Science and Technology* **118**, 14–29. <https://doi.org/10.1016/j.coldregions.2015.06.009>.
- Irannezhad, M., Ronkanen, A.-K. & Kløve, B. 2016 Wintertime climate factors controlling snow resource decline in Finland. *International Journal of Climatology* **36** (1), 110–131. <https://doi.org/https://doi.org/10.1002/joc.4332>.
- Irannezhad, M., Ronkanen, A.-K., Kiani, S., Chen, D. & Kløve, B. 2017 Long-term variability and trends in annual snowfall/total precipitation ratio in Finland and the role of atmospheric circulation patterns. *Cold Regions Science and Technology* **143**, 23–31. <https://doi.org/https://doi.org/10.1016/j.coldregions.2017.08.008>.
- Irannezhad, M., Minaei, M., Ahmadian, S. & Chen, D. 2018 Impacts of changes in climate and land cover-land use on flood characteristics in Gorganrood Watershed (Northeastern Iran) during recent decades. *Geografiska Annaler: Series A, Physical Geography* **100** (4), 340–350. <https://doi.org/10.1080/04353676.2018.1515578>.
- Irannezhad, M., Ahmadi, B., Liu, J., Chen, D. & Matthews, J. H. 2022a Global water security: A shining star in the dark sky of achieving the sustainable development goals. *Sustainable Horizons* **1**, 100005. <https://doi.org/https://doi.org/10.1016/j.horiz.2021.100005>.
- Irannezhad, M., Ahmadian, S., Sadeqi, A., Minaei, M., Ahmadi, B. & Marttila, H. 2022b Peak spring flood discharge magnitude and timing in natural rivers across Northern Finland: Long-term variability, trends, and links to climate teleconnections. *Water* **14**, 1312.
- Irannezhad, M., Abdulghafour, Z. & Sadeqi, A. 2024 Climate teleconnections influencing historical variations, trends, and shifts in snow cover days in Finland. *Earth Systems and Environment*. <https://doi.org/10.1007/s41748-024-00466-1>
- Jaagus, J. 2006 Climatic changes in Estonia during the second half of the 20th century in relationship with changes in large-scale atmospheric circulation. *Theoretical and Applied Climatology* **83** (1), 77–88. <https://doi.org/10.1007/s00704-005-0161-0>.
- Jansson, P., Hock, R. & Schneider, T. 2003 The concept of glacier storage: A review. *Journal of Hydrology* **282** (1), 116–129. [https://doi.org/10.1016/S0022-1694\(03\)00258-0](https://doi.org/10.1016/S0022-1694(03)00258-0).
- Käyhkö, J. 2004 Muuttuuko pohjolan ilmasto? (Fennoscandian climate in change?). *Publications of Geography Department of the University of Turku* **168**, 19–35.
- Konapala, G., Mishra, A. K., Wada, Y. & Mann, M. E. 2020 Climate change will affect global water availability through compounding changes in seasonal precipitation and evaporation. *Nature Communications* **11** (1), 3044. <https://doi.org/10.1038/s41467-020-16757-w>.
- Korhonen, J. 2006 Long-term changes in lake ice cover in Finland. *Hydrology Research* **37** (4–5), 347–363. <https://doi.org/10.2166/nh.2006.019>.
- Korhonen, J. & Kuusisto, E. 2010 Long-term changes in the discharge regime in Finland. *Hydrology Research* **41** (3–4), 253–268. <https://doi.org/10.2166/nh.2010.112>.
- Lim, Y. K. & Kim, H. D. 2013 Impact of the dominant large-scale teleconnections on winter temperature variability over East Asia, *Journal of Geophysical Research Atmospheres* <https://doi.org/10.1002/jgrd.50462>.
- Mann, H. B. 1945 Non-parametric test against trend. *Econometrica* **13** (3), 245–259.
- Marttila, H., Huuki, H., Bin, A. F., Patro, E. R., Hellsten, S., Ruokamo, E., Karhinen, S., Romakkaniemi, A., Kopsakangas-Savolainen, M., Pongracz, E., Virk, Z. T., Haghighi, A. T. & Juutinen, A. 2024 River systems under peaked stress. *Environmental Research Letters* **19** (6), 64071. <https://doi.org/10.1088/1748-9326/ad4db9>.
- Meriö, L.-J., Ala-aho, P., Linjama, J., Hjort, J., Kløve, B. & Marttila, H. 2019 Snow to precipitation ratio controls catchment storage and summer flows in boreal headwater catchments. *Water Resources Research* **55** (5), 4096–4109. <https://doi.org/https://doi.org/10.1029/2018WR023031>.
- Mikkonen, S., Laine, M., Mäkelä, H. M., Gregow, H., Tuomenvirta, H., Lahtinen, M. & Laaksonen, A. 2015 Trends in the average temperature in Finland, 1847–2013. *Stochastic Environmental Research and Risk Assessment* **29** (6), 1521–1529. <https://doi.org/10.1007/s00477-014-0992-2>.
- Minaei, M. & Irannezhad, M. 2018 Spatio-temporal trend analysis of precipitation, temperature, and river discharge in the northeast of Iran in recent decades. *Theoretical and Applied Climatology* **131** (1), 167–179. <https://doi.org/10.1007/s00704-016-1963-y>.
- Okkonen, J. & Kløve, B. 2010 A conceptual and statistical approach for the analysis of climate impact on ground water table fluctuation patterns in cold conditions. *Journal of Hydrology* **388** (1), 1–12. <https://doi.org/https://doi.org/10.1016/j.jhydrol.2010.02.015>.
- Park, E. & Lee, Y. J. 2001 Estimates of standard deviation of Spearman's rank correlation coefficients with dependent observations. *Communications in Statistics Part B: Simulation and Computation* <https://doi.org/10.1081/SAC-100001863>.
- Pirinen, P., Simola, H., Aalto, J., Kaukoranta, J. P., Karlsson, P. & Ruuhela, R. 2012 *Tilastoja Suomen Ilmastosta 1981–2010*
- Pohl, S., Davison, B., Marsh, P. & Pietroniro, A. 2005 Modelling spatially distributed snowmelt and meltwater runoff in a small Arctic catchment with a hydrology land-surface scheme (WATCLASS). *Atmosphere-Ocean* **43** (3), 193–211. <https://doi.org/10.3137/ao.430301>.

- Räisänen, J. 2008 Warmer climate: Less or more snow?. *Climate Dynamics* **30** (2), 307–319. <https://doi.org/10.1007/s00382-007-0289-y>.
- Rawlins, M. A., Ye, H., Yang, D., Shiklomanov, A. & McDonald, K. C. 2009 Divergence in seasonal hydrology across northern Eurasia: Emerging trends and water cycle linkages. *Journal of Geophysical Research: Atmospheres* **114** (D18). <https://doi.org/10.1029/2009JD011747>.
- Sen, P. K. 1968 Estimates of the regression coefficient based on Kendall's Tau. *Journal of the American Statistical Association* <https://doi.org/10.1080/01621459.1968.10480934>.
- Serreze, M. C., Walsh, J. E., Chapin, F. S., Osterkamp, T., Dyurgerov, M., Romanovsky, V., Oechel, W. C., Morison, J., Zhang, T. & Barry, R. G. 2000 Observational evidence of recent change in the northern high-latitude environment. *Climatic Change* **46** (1), 159–207. <https://doi.org/10.1023/A:1005504031923>.
- Thompson, D. W. J. & Wallace, J. M. 1998 The Arctic oscillation signature in the wintertime geopotential height and temperature fields. *Geophysical Research Letters* <https://doi.org/10.1029/98GL00950>.
- UN 2015 *About the Sustainable Development Goals – United Nations Sustainable Development Sustainable Development Goals*.
- Uvo, C. B., Foster, K. & Olsson, J. 2021 The spatio-temporal influence of atmospheric teleconnection patterns on hydrology in Sweden. *Journal of Hydrology: Regional Studies* **34**, 100782. <https://doi.org/10.1016/j.ejrh.2021.100782>.
- Virk, Z. T., Ashraf, F. B., Haghighi, A. T., Kløve, B., Hellsten, S. & Marttila, H. 2024 Nordic socio-recreational ecosystem services in a hydropeaked river. *Science of The Total Environment*, **912**, 169385. <https://doi.org/10.1016/j.scitotenv.2023.169385>.
- Wanders, N. & Wada, Y. 2015 Decadal predictability of river discharge with climate oscillations over the 20th and early 21st century. *Geophysical Research Letters* **42** (24), 10,610–689,695. <https://doi.org/10.1002/2015GL066929>.
- Wang, D., Wang, C., Yang, X. & Lu, J. 2005 Winter northern hemisphere surface air temperature variability associated with the Arctic Oscillation and North Atlantic Oscillation. *Geophysical Research Letters* **32** (16). <https://doi.org/10.1029/2005GL022952>.
- Wilson, D., Hisdal, H. & Lawrence, D. 2010 Has streamflow changed in the Nordic countries? Recent trends and comparisons to hydrological projections. *Journal of Hydrology* **394** (3), 334–346. <https://doi.org/10.1016/j.jhydrol.2010.09.010>.
- Yue, S., Pilon, P., Phinney, B. & Cavadas, G. 2002 The influence of autocorrelation on the ability to detect trend in hydrological series. *Hydrological Processes* <https://doi.org/10.1002/hyp.1095>.

First received 18 March 2024; accepted in revised form 20 August 2024. Available online 6 September 2024



Society of Petroleum Engineers

SPE-224993-MS

Towards Autonomous Rotary Drilling System: A Robust Rate of Penetration Model for Drilling Operation Using Artificial Intelligence

R. M. Elgaddafi, Petroleum engineering department, Australian University - Kuwait, Kuwait City, Kuwait / Petroleum engineering department, University of Oklahoma, Norman, OK, USA; K. Amadi, B. M. Biltayib, M. T. Al Saba, and M. Omar, Petroleum engineering department, Australian University - Kuwait, Kuwait City, Kuwait; A. Dashti, Petroleum engineering department, Australian University - Kuwait, Kuwait City, Kuwait / Kuwait Oil Company, Kuwait City, Kuwait; M. Alali, Petroleum engineering department, Australian University - Kuwait, Kuwait City, Kuwait / Kuwait Oil Company, Kuwait City, Kuwait; M. Alabdullah, Petroleum engineering department, Australian University - Kuwait, Kuwait City, Kuwait / Kuwait Oil Company, Kuwait City, Kuwait

Copyright 2025, Society of Petroleum Engineers DOI [10.2118/224993-MS](https://doi.org/10.2118/224993-MS)

This paper was prepared for presentation at the SPE Conference at Oman Petroleum & Energy Show held in Muscat, Oman, 12 - 14 May 2025.

This paper was selected for presentation by an SPE program committee following review of information contained in an abstract submitted by the author(s). Contents of the paper have not been reviewed by the Society of Petroleum Engineers and are subject to correction by the author(s). The material does not necessarily reflect any position of the Society of Petroleum Engineers, its officers, or members. Electronic reproduction, distribution, or storage of any part of this paper without the written consent of the Society of Petroleum Engineers is prohibited. Permission to reproduce in print is restricted to an abstract of not more than 300 words; illustrations may not be copied. The abstract must contain conspicuous acknowledgment of SPE copyright.

Abstract

The assessment of drilling efficiency is strongly related to the rate of penetration (ROP) which is a vital parameter in evaluating the success of a drilling operation. Traditionally, the oil industry relies on the driller's experience in selecting optimum operating parameters while drilling wells. An autonomous rotary drilling system with optimized ROP is the solution to mitigate drilling risks and reduce overall drilling costs. Developing a robust ROP model is a crucial step in optimizing its value and ultimately enhancing drilling efficiency. This study aimed to develop a predictive ROP model that uses direct and derived drilling parameters leveraging various machine learning algorithms, thereby providing a tool for drilling engineers to anticipate drilling performance and make data-driven operational decisions.

A dataset of 6,279 measured ROP data points was gathered from five wells in the Volve Field, along with corresponding drilling parameters and real-time measurements. These parameters include weight on bit (WOB), rotary pipe speed (RPM), surface torque, pump pressure, mud flow rate, and equivalent circulating density (ECD). Additionally, derived controllable and uncontrollable variables, such as unconfined compressive strength (UCS), drilling mechanical specific energy (DMSE), and feed thrust force (FET), were computed using well-established correlations. First, data analytics and exploratory visualization are conducted to clean up the dataset and discover the relationship between ROP and feature inputs. Besides, a feature variable-importance analysis is implemented to identify the most crucial parameters affecting the ROP. For model development, five supervised regression machine learning algorithms were utilized. Additionally, in this study, the ROP model is developed as a function of drilling mechanical specific energy (DMSE), and feed thrust (FET). A comparative study of ROP predictions from the two approaches (surface operating and energy parameters) is presented.

This study presents a robust predictive model for accurately predicting the rate of penetration (ROP) using derived controllable drilling variables. The developed model addresses the limitations of conventional approaches and mitigates the uncertainties associated with empirical correlations. The findings offer valuable insights for the oil and gas industry, as precise ROP predictions contribute to improved drilling efficiency, particularly in complex operations, while also reducing overall drilling costs.

Drilling operation is considered the most expensive stage in developing the oil and gas fields due to the challenges encountered by the drillers throughout the process. To increase the economic feasibility of oil and gas projects, numerous drilling practices are carried out to lessen drilling operating cost. The main principle of these methods is aimed at professionally improving the drilling rate of penetration with minimum affordable required mechanical energy (Dupriest and Koederitz, 2005; Li et al., 2015; Moraveji and Naderi, 2016; Chen et al., 2016a, 2016b; Hegde and Gray, 2017, 2018). Additionally, for the past few decades, a significant effort has been made by operators, researchers and engineers to enhance the drilling performance by optimizing the rate of penetration (ROP). Optimizing the ROP requires a comprehensive understanding of the mechanism of drilling process and mechanical properties of the drilled formation. ROP is defined as the rate at which the wellbore deepens towards the targeted objective as the drilling operation progresses (Ahmed et al., 2019; Hegde et al., 2017; Pacis et al., 2023). Previous studies (Alavi Nezhad Khalil Abad et al., 2023; Barbosa et al., 2019; Hegde et al., 2017; Pacis et al., 2023; Riazi et al., 2022) reported the influential factors on the ROP value of drilling operations and classified them into controllable and uncontrollable variables. The controllable factors consist of drilling parameters (weight on bit (WOB), rotary drilling string speed (RPM), fluid flow rate, and bit type) and fluid properties (drilling fluid density and rheology). Meanwhile, geological formation features and its mechanical characteristics are classified as uncontrollable variables, as shown in Fig.1.

Factors Affecting Drilling Rate of Penetration		
Controllable factors – drilling parameters • Weight on bit (WOB) • Rotary speed (RPM) • Mud flow rate • Bit type & hydraulics • Surface torque	Controllable factors – fluid properties • Mud weight (density) • Plastic viscosity • Yield stress	Uncontrollable factors • Rock uniaxial Compressive Strength (UCS) • Rock porosity • Rock Hardness • In-situ stresses • Pore pressure • Formation matrix

Figure 1—Major factors affecting drilling rate of penetration (ROP).

In the conventional manual drilling system, the driller is responsible for managing the operation by expertly adjusting the top-drive's rotary speed and the draw-work's axial force (Amadi et al., 2023) to optimize ROP. Therefore, gaining a deeper understanding of the relationship between the rate of penetration (ROP), weight on bit (WOB), and rotary speed (RPM) is a critical step toward improving drilling efficiency. Figure 2a demonstrates the bit efficiency in terms of ROP with the incremental variation in the WOB and determines threshold and founder points for applied minimum and maximum WOB. Above the threshold, in region II (efficient bit), the ROP increases linearly with the increasing of the WOB. However, beyond the founder point, a further boosting the weight on bit results in relatively minor improvement or even reduction in the ROP (Robinson and Ramsey, 2001). Operating between the threshold and founder points can extend the bit performance life and reduce bit wearing and balling damages. A direct relationship between ROP and drilling string rotary speed for different types of formations is presented in Figure 2b. As displayed in the figure, the ROP increases linearly with the increase of the rotary speed for the soft formation. However, it is not directly visible in hard formations at high RPM where the rise in the ROP diminishes (Paone et al. 1966; Hossain and Al-Majed 2015).

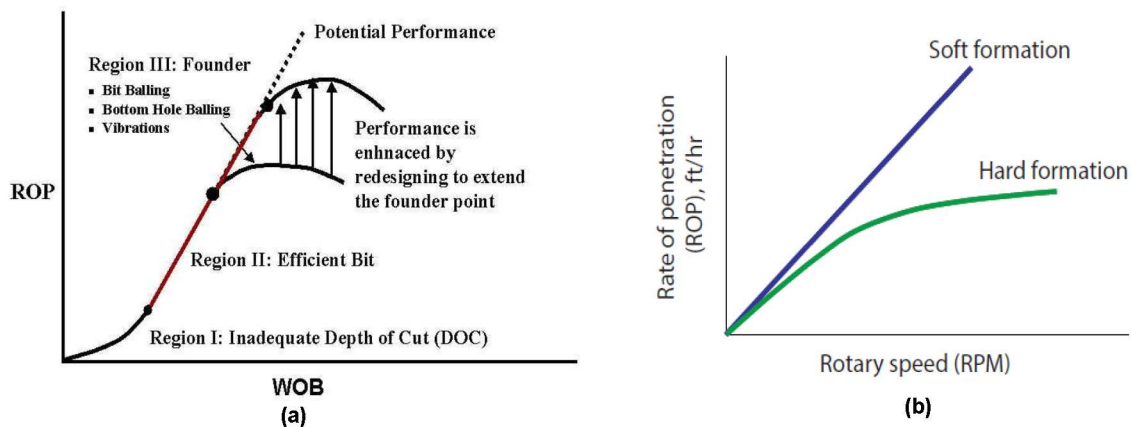


Figure 2—Relationship between drilling rate of penetration (ROP) and controllable parameters: a) ROP vs. WOB (Dupriest and Koederitz 2005); and b) ROP vs. RPM

An extraordinary endeavor has been undertaken by researchers and field engineers in modeling the optimum ROP value. In regards, two different approaches: analytical (physics base or empirical) models and data-driven (machine learning) models are exploited to regulate the optimal drilling control surface parameters such as weight-on-bit (WOB), torque, and rotary speed (RPM). For past decades, numerous traditional models were developed to predict ROP and optimize the drilling performance (Soares et al. 2016). The most pioneering and commonly used empirical models are Graham and Muench model, Maurer model, Maurer (1962), Bingham model, Bingham (1965), Warren model, Warren (1984), Bourgoyne and Young model, Bourgoyne and Young (1974), Soares and Gray (2019). These models are formulated as a function of several drilling surface features. The drawback of these models is that their formulas consisted of empirical coefficients (constants) which are determined based on laboratory experiments or incomplete field data (Hadi 2015; Riazi et al. 2022). Moreover, none of the developed models compiles the effect of all contributing drilling parameters for ROP prediction. Each model considers selected parameters and disregards the others. These malfunctions in the existing model development have led to a lack of comprehensive models and provide low to moderate accuracy in predicted ROP value (Khalilidermani and Kenz 2023; Hegde et al. 2017). A summary of the most used traditional ROP models is presented in Table 1.

Table 1—Summary of selected empirical ROP models with features considered in each model development.

References	Formula	Controllable and uncontrollable parameters
Maurer (1962)	$ROP = \frac{K}{S^2} \left(\frac{WOB}{d_{bit}} - \frac{WOB_0}{d_{bit}} \right)^2 RPM$	Weight on the bit (WOB), rotational speed (RPM), and diameter of bit (d_{bit})
Galle and Woods (1963)	$ROP \propto \left(\frac{1}{0.928125h^2 + 6h + 1} \right)^{b7}$	Bit-tooth wear (h)
Bingham (1965)	$ROP = K \left(\frac{WOB}{d_{bit}} \right)^{b5} RPM$	Weight on the bit (WOB), rotational speed (RPM), diameter of bit (d_{bit}) and rock strength
Bourgoyne and Young (1974)	$ROP = \frac{dD}{dt} = \exp \left(a_1 + \sum_{j=2}^{j=8} a_j x_j \right)$	Weight on the bit (WOB), rotational speed (RPM), diameter of bit (d_{bit}), rock strength, Bit-tooth wear (h), fluid motion force beneath the bit, true vertical depth, bearing wear, mud density, mud pressure and pore pressure
Reza and Alcocer (1986)	$\frac{ROP}{RPM d_{bd}} = K \left[\frac{RPM d_{bd}^2}{9} \right]^a \left[\frac{RPM d_{bd}^3}{Q} \right]^b \left[\frac{Ed_{bd}}{WOB} \right]^c \left[\frac{\Delta P d_{bd}}{WOB} \right]^d$	Weight on the bit (WOB), rotational speed (RPM), Bit-tooth wear (h), mud viscosity, bearing wear, flow rate, mud pressure, rock hardness and pore pressure
Hareland and Rampersad (1994)	$ROP = W_f \left[f_c(P_e) \left(\frac{aS^2 d_{bit}^3}{RPM^b WOB^2} + \frac{b}{RPM d_{bit}} + \frac{cd_{bit} \rho_f \mu}{F_{jet}} \right) \right]$	Weight on the bit (WOB), rotational speed (RPM), and diameter of bit (d_{bit}), Bit-tooth wear (h), fluid motion force beneath the bit, viscosity, fluid density, rock strength, and pore pressure.
Motahari et al. (2010)	$ROP = W_f \left(\frac{RPM^3 WOB^a}{d_{bit} UCS} \right)$	Weight on the bit (WOB), rotational speed (RPM), rock strength, and diameter of bit (d_{bit}).

As a significant step toward the digitalization of oil and gas fields, data-driven models have been widely suggested by researchers for accurately predicting the rate of penetration (ROP). The development of artificial intelligence (AI) aims to overcome the limitations of traditional physics-based ROP models (Khoukhi and Ibrahim, 2012). During drilling operations, vast amounts of real-time surface data are continuously collected. Leveraging AI enables engineers to analyze this data comprehensively, extract valuable insights, and identify the most influential drilling parameters affecting ROP. According to the literature survey, artificial neural networks (ANNs) have been extensively adopted for ROP modeling due to their ability to capture complex relationships between input features and their adaptive learning capabilities (Bilgesu et al., 2017; Moran et al., 2010; Jiang and Samuel, 2016; Bhowmik et al., 2017; Arabjamaloei and Shadizadeh, 2011; Bataee and Mohseni, 2011; Bezminabadi et al., 2017; Delavar et al., 2023; Elkhatatny, 2019). These models commonly correlate ROP with real-time surface drilling parameters. However, inconsistencies exist among studies regarding the number and type of input features used, ranging from five to ten parameters, as well as differences in problem-solving techniques, including traditional methods and genetic algorithms. Beyond ANN, other machine learning approaches, such as supervised Support Vector Machine (SVM), have also been successfully employed for ROP modeling. Several studies (Bodaghi et al., 2015; Ahmed et al., 2018, 2019) compared SVM to alternative algorithms such as Back Propagation Neural Network (BPNN), Least Squares Support Vector Regression (LS-SVR), Extreme Learning Machine (ELM), and ANN. Their findings revealed that LS-SVR and SVM outperformed BPNN and ELM in ROP prediction. A comprehensive summary of major studies related to ROP prediction using

data-driven methods, along with their respective model parameters, is provided elsewhere (Amadi et al., 2023; Khalilidermani and Kenz, 2022, 2023).

For decades, drilling efficiency has primarily been assessed based on optimizing the rate of penetration (ROP), which is largely controlled by the driller or operator. However, relying solely on ROP as an indicator of drilling efficiency may no longer be sufficient. In recent years, the concept of mechanical specific energy (MSE) has emerged as a fundamental principle for evaluating drilling performance. The concept of mechanical specific energy (MSE) was first introduced by Teale (1965) and defined as the amount of mechanical energy required to excavate a unit volume of rock. Similar to the aforementioned ROP models, two different approaches, mathematical and data-driven (AI) models, are utilized to calculate the mechanical specific energy. For MSE mathematical models, Teale (1965) was a pioneer investigator for developing the first MSE model for conventional rotary systems. The proposed model incorporates the most critical controllable drilling parameters including weight on bit, surface torque, rotational speed, and bit diameter. Accordingly, the MSE is given as follows:

$$\text{MSE} = \frac{4 \times \text{WOB}}{\pi d_{\text{bit}}^2} + \frac{480 \times \text{TOR} \times \text{RPM}}{d_{\text{bit}}^2 \times \text{ROP}} \quad \text{Eqn. (1)}$$

In Eqn. (1), WOB refers to the weight on bit, TOR is surface torque, RPM is a rotational speed, ROP is rate of penetration, and d_{bit} is the hole diameter. Subsequently, other investigators modified and extent Teale's model to account for different aspects of drilling factors such as mechanical bit efficiency, hydraulic energy, and difference between downhole and surface TOB and WOB (Amadi et al. 2012; Dupriest et al. 2005; Hammoutene and Bits 2012; Mohan et al. 2009 and 2015; Chen et al. 2014). An extensive summary of MSE mathematical models developed for vertical, direction and horizontal wells is discussed deeply elsewhere (Chen et al. 2018). On the other hand, several studies (Anemangely et al. 2018; Hegde and Gray 2018; Liang et al. 2022) are conducted to develop data-driven MSE models using various AI algorithms. The MSE prediction is utilized to identify the formation lithology ahead of the drill bit and determine the properties of underlaying rocks such as Poisson ratio, uniaxial compressive strength (UCS), confining compressive strength (CCS). Consistently, combined data-driven MSE models with optimization methods have been suggested for forecasting the optimal values of rotary speed, WOB and ROP (Delavar et al. 2023; Al Hamlawi et al. 2021).

In general, the main target of the operators is optimizing the drilling operation which is typically undertaken by optimizing the rate of penetration (ROP). However, it is vital to highlight that the optimization of drilling process is not simply attained by obtaining high ROP. The process of ROP optimization requires an accurate predictive ROP model, serving as a cost function, that comprehensively considers all influential drilling parameters. Besides, nominating number and types of constraints for the optimization process is very critical key for attaining high drilling efficiency. As per forementioned studies, numerous mathematical and data-driven models are developed to construct a robust relationship between ROP and real-time drilling parameters. However, limited studies (Amadi et al. 2023; Chen et al. 2014; Mantegazini et al. 2024) are coupled the rate of penetration (ROP) optimization to the mechanical specific energy (MSE). Chen et al. (2014) developed a physical-based model for predicting ROP based on mechanical specific energy. The model assumes that MSE is equal to the confining compressive strength (CCS) of the formation. Recently, a novel data-driven model (ANN algorithm) for predicting ROP is proposed Amadi et al. (2023). The input features into the proposed model encompassed two derived controllable parameters such as drilling mechanical specific energy (DMSE) and feed thrust force (FET). Mantegazini et al. (2024) proved that concept of coupling MSE and ROP is the best technique to identify the optimum ROP and evaluate the drilling efficiency.

As an initial step toward ROP optimization, this study aims to develop a robust data-driven model for accurately predicting ROP using AI techniques. Additionally, it seeks to validate the hypothesis that the combination of high ROP and low MSE serves as the most effective criterion for assessing drilling

efficiency. The model development follows two distinct approaches. The first approach integrates derived controllable drilling parameters, including drilling mechanical specific energy (DMSE) and feed thrust force (FET) for predicting ROP value. The second approach employs a conventional data-driven ROP model that correlates ROP with real-time controllable and uncontrollable drilling parameters. Both approaches utilize five supervised regression machine learning algorithms. Furthermore, this research explores the capability of various machine learning algorithms in capturing and simulating the complex relationship between ROP and hydro-mechanical drilling parameters.

Data acquisition and preparation

A field database for actual drilling operation was collected from Volve Field on the Norwegian continental self-released by Equinor ASA (Gupta et al. 2020). The data set represents a sandstone rock reservoir (formation named Hugin) interval drilled in this field. The collected data encompassed a large openhole and MWD logs for 12 wells. The openhole logs consist of density, neutron, gamma ray, and sonic logs. whilst MWD logs include a variety of surface drilling measurements such as WOB, RPM, surface torque, ROP, ECD, bottom hole pressure and temperature, pump pressure, and mud flow rate. As a first step in the data preparation, the relationship between the input features and targeted/predicted variable (ROP) is investigated using a graphical representation tool. Next, a number of secondary derived variables which are used as input controllable or/and uncontrollable features for the ROP model (UCS, DMSE, and FET) are accurately computed using well established equations. The calculation procedure of these variables used in this study is elaborated as follows:

Uniaxial compressive strength (UCS)

Uniaxial compressive strength (UCS) is a vital quantity in geomechanics, representing the strength of the rock formation, which directly influences drilling efficiency and rate of penetration (ROP). Considering the UCS as one of uncontrollable input features in data-driven model can significantly improve ROP forecasting while drilling across diverse geological formations. It is important to emphasize that UCS is not a direct measured variable. However, it can be computed using existing empirical correlations or data-driven models (Amadi et al. 2023; Oyler et al. 2010). As the reservoir formation consists of sandstone rock, the UCS is computed as follows (Oyler et al. 2010):

$$UCS = 468000e^{-0.054 \times \Delta t} \quad \text{Eqn. (2)}$$

In Eqn. (2) Δt represents a travel time of P-wave (microsec/ft) which is excluded from sonic log measurement.

Drilling mechanical specific energy (DMSE)

Drilling Mechanical Specific Energy (DMSE) is an essential measure of the drilling process's energy efficiency. Drilling operations can be made more economical, faster, and efficient by monitoring and enhancing DMSE. It is a measurement of the amount of energy necessary for drilling through a formation at a specific rate of penetration (ROP). As forementioned in the MSE modeling survey, numerous mathematical models were developed for predicting MSE. In this study, MSE value is computed by adopting the equation instituted by several scholars (Amadi et al. 2023; Dupriest et al. 2005; Cherif et al. 2012).

$$DMSE = \left(\frac{480 \times TOR \times RPM}{D^2 \times ROP} + \frac{4WOB}{\pi \times D^2} \right) \times E_m \quad \text{Eqn. (3)}$$

In Eqn. (3), TOR refers to surface torque, RPM is rotational speed (rev./min), WOB is weight on bit, D is diameter of bit size (in), ROP is rate of penetration (ft/hr). To account for the mechanical efficiency drill bit, a bit factor (E_m) is introduced to Teale's equation (Eqn.1). E_m possesses different values, depending

on bit type. It equals 0.125 for PDC, and 0.25 for roller cone. In the current study, the bit Factor value is undertaken as 0.125 (Amadi et al. 2023).

Feed thrust force

Feed Thrust (FET) is the force that maintains contact between the drill bit and the rock formation during drilling operation. The distance the drilling line is discharged by the draw-work hoisting mechanism often governs or dictates it. It serves as a surrogate for axial thrust or weight on bit (WOB). The concept of FET was first invented by Lindqvist (1982) and Sinkala (1989). Later, Cavanough et al. (2008) utilized the FET concept while developing a self-optimizing control system for hard rock percussive drilling. The FET is computed using the following equation (Amadi et al. 2023):

$$FET = \frac{3}{2} \frac{TOR}{d_{bit}} \frac{\phi - 2v}{\sqrt{\phi v - v^2}} \quad \text{Eqn. (4)}$$

FET is the Feed thrust force, TOR is the torque on the surface, ϕ implies the radius of the cutter, v refers to penetration rate per revolution, d_{bit} is diameter of the drill bit.

Methodology

According to the literature, the magnitude of the drilling rate of penetration (ROP) has been modeled using both empirical correlations and data-driven approaches. Most artificial intelligence (AI) models predict ROP by correlating it with direct drilling parameters, primarily using artificial neural networks (ANN). In this study, a robust AI-based tool is employed to develop a data-driven model for forecasting ROP as a function of input features. Two modeling approaches are considered. In the first approach, simultaneous mechanical drilling parameters and geological rock properties, specifically unconfined compressive strength (UCS), are used as input variables. In the second approach, only derived controllable variables, namely DMSE and FET, serve as input features. The step-by-step formulation procedure for both cases is elaborated below.

Exploratory data analysis and pre-processing

Data pre-processing is an essential stage in the machine learning model development. This stage encompasses data visualization and statistical analysis process which are aimed at assessing the quality of the data and discovering the nature of the database. Statistical analysis provides insights into the database which identifies the minimum and maximum values of the input features. The visualization of the data helps to provide a better interpretation of the model predictions. Figure 3 presents a scatter matrix of mechanical controllable and uncontrollable features in the gathered dataset and corresponding ROP. Prior to model development, the dataset was first scrutinized for irregularities, such as negative values and outliers. Boxplots for real-time drilling parameters are developed and presented in Fig.4. As displayed from the figure, potential outliers, including negative values in Weight on Bit (WOB) and Torque are observed. These values are physically implausible for drilling operations. These outliers and unreasonable values are excluded from the database to evade weaknesses in the model development. By removing the outliers, a clean and vigorous database is created.

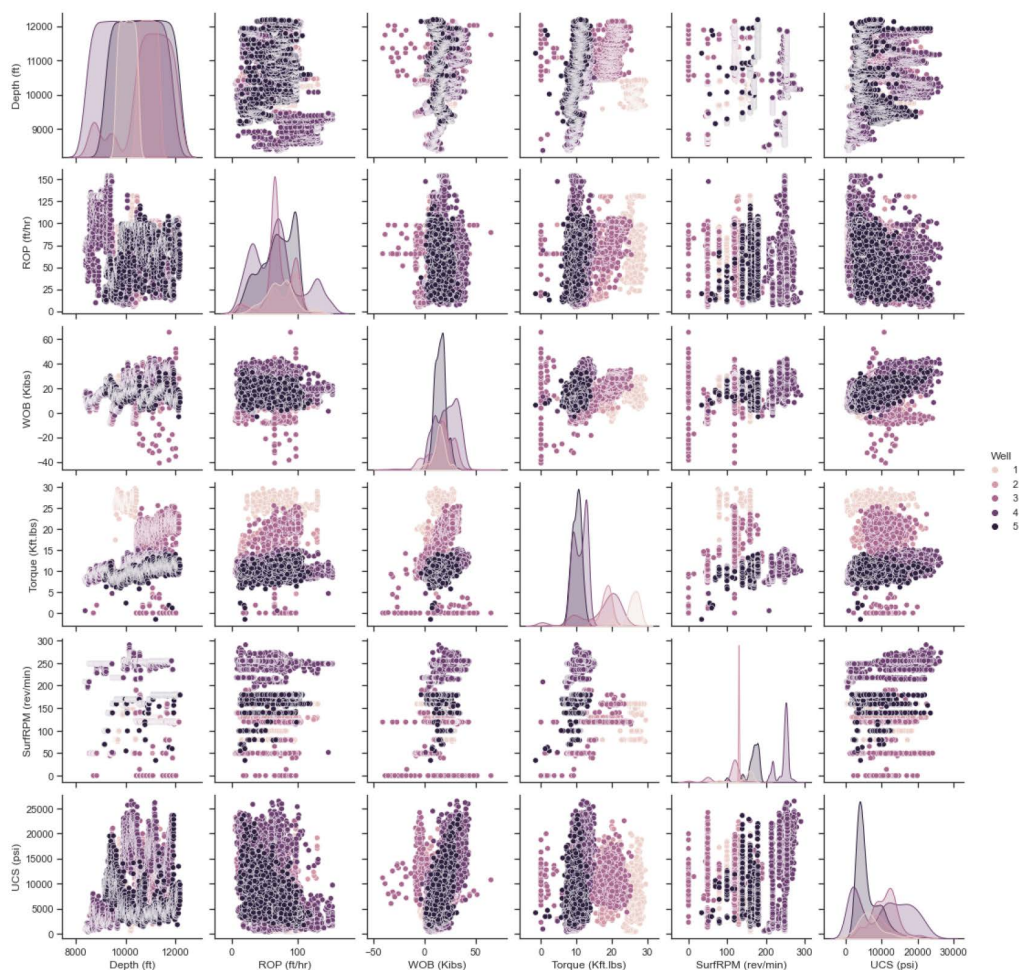


Figure 3—Scatter matrix of chosen features in the collected dataset and corresponding drilling rate of penetration

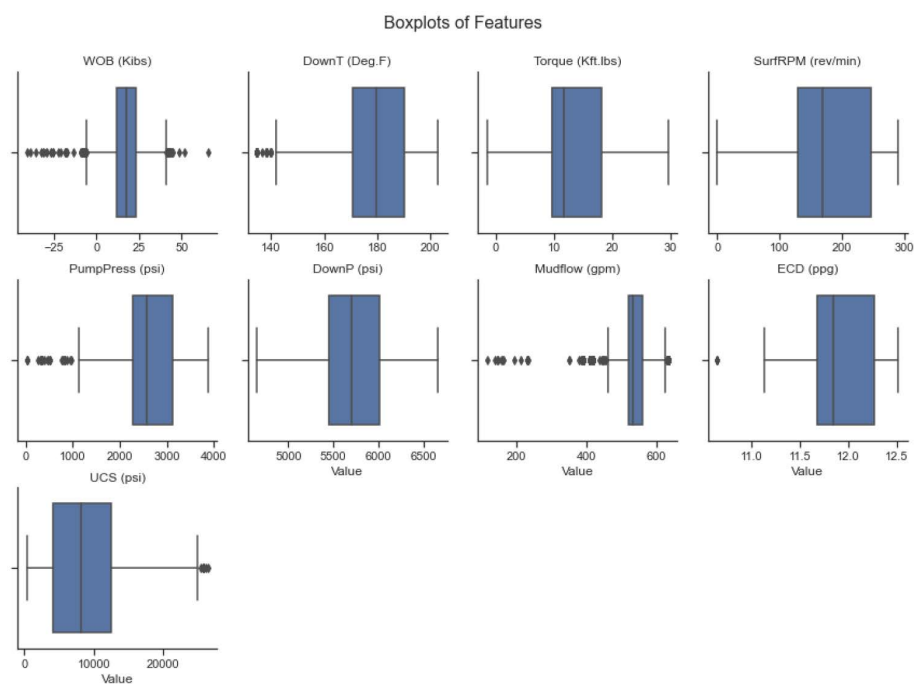


Figure 4—Boxplots for real-time drilling parameters (input features)

In this study, five cutting-edge supervised regression machine-learning algorithms are utilized to discover insights into the drilling operation and develop a robust ROP model. The regression algorithms include Support Vector Machine (SVM), Random Forest (RF), Extra Tree (ET), Extreme Gradient Boosting method (XGBoost), and CatBoost (CB). The basic and working mechanism of the applied algorithms are presented elsewhere (Hafsa et al. 2023; Rushd et al. 2021).

In any ML application, after training and optimizing the employed algorithm, it is a very essential step to process the evaluation metrics to determine the accuracy of the model prediction. The ML regression algorithm's performance is assessed using four evaluation metrics including Mean Squared Error (MSE), Mean Absolute Error (MAE), coefficient of determination (R^2), and Root Mean Squared Error (RMSE). The metrics quantitatively compute the deviation of the predicted from the actual ROP value. In the present study, the coefficient of determination (R^2) is computed for training and testing datasets. The best model is selected based on the one that has a root-mean square error of zero and a minor difference between training and testing R^2 . Brief descriptions of these statistical metrics and their formulations are discussed elsewhere (Elgaddafi et al. 2023).

Machine Learning Model Development – Training and Testing. This section presents the modeling procedure of various machine learning algorithms employed in this study. The predictive power of selected machine learning algorithms was evaluated by training and testing five regression-supervised models to forecast the rate of penetration (ROP) utilizing most effective input features. The selected features represent drilling operation conditions and rock characteristics. As a first step, database is collected from aforementioned field consisting of mechanical drilling parameters, MWM and lithology logs, and reservoir rock characteristics. Secondly, the derived controllable and uncontrollable variables (DMSE, FET, and UCS) are accurately computed using Eqns. (2 – 4). As a third step, pre-processing data is implemented by constructing scatter plots and boxplots (Figs. 3 and 4). The benefit of analyzing the gathered data is to draw insights into and explore the nature of the relationship between the input features and the predicted variable. Subsequent pre-processing step, input features and output (predicted target) are identified and normalized using MaxMin. scaler. As a typical standard of using any ML techniques, the cleaned database is split into training set containing 80% of the samples and a test set containing the residual 20% of the data. The training procedure of five ML models is fulfilled using the training data points whilst test data was exploited as independent data for validation. Then, the trained algorithms were assessed by feeding them with a test data set and computing the evaluation metrics used in this study. The ML modeling procedure is summarized in the schematic of ROP model development that is presented in Figure 5. The following phase is optimizing the algorithm parameters to acquire the best prediction for the used algorithm. This step is known as a hyper-tuning process. A grid search feature was used using the training segment of the dataset to find the most optimized parameters for each ML algorithm. The five proposed machine learning algorithms were re-trained using the newly optimized parameters in the next step.

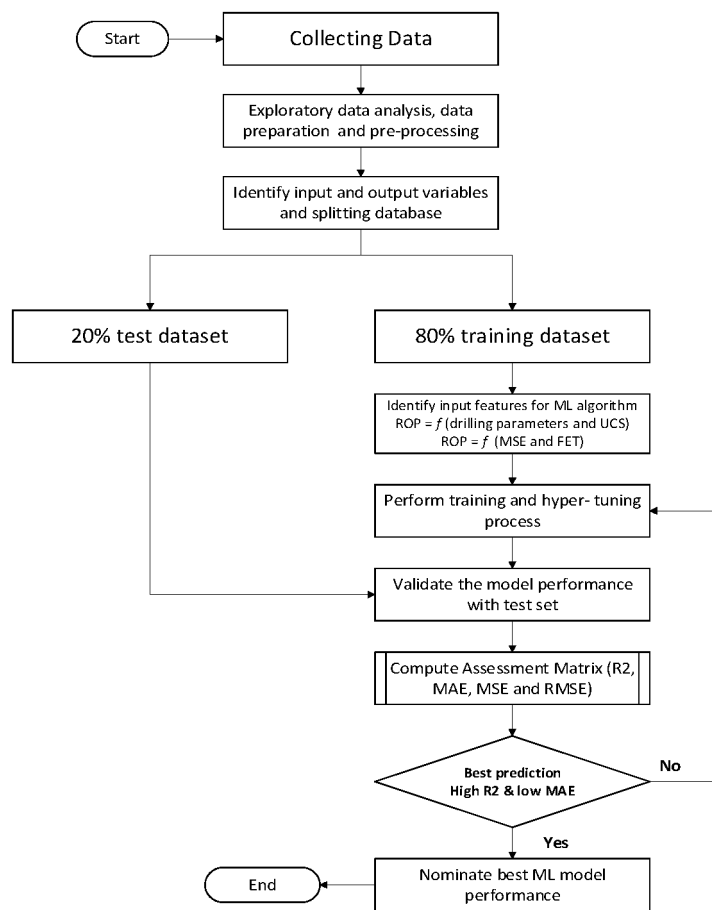


Figure 5—Schematic of ROP model development procedure using machine learning techniques

Results and discussion

This section presents the outcomes of applying various regression-based supervised machine learning algorithms to model the drilling rate of penetration (ROP) using two approaches: direct surface drilling parameters and derived controllable variables (DMSE and FET). The algorithms were first trained and optimized before being utilized to predict ROP variation with depth.

Analysis of Model Performance

The evaluation results of the models obtained from trained and tested five different algorithms on the complete dataset are presented in Tables 2 and 3. For both modeling approaches, the supervised regression models can be ranked in terms of accuracy for predicting the rate of penetration (ROP) as follows: Extra Trees (ET), CatBoost (CB), Random Forest (RF), Gradient Boosting (GB), and Support Vector Machine (SVM). As shown in the tables, the SVM model demonstrated poor accuracy during both the training and testing phases for both modeling approaches. In contrast, the other four machine learning models (ET, CB, RF, and GB) performed reasonably well in correlating ROP with real-time drilling parameters. However, a noticeable drop in accuracy was observed when these models were validated with test dataset. Despite this decline in the accuracy, the four models (ET, CB, RF, and GB) provided relatively strong predictive performance when DMSE and FET were used as input features. For example, the CB algorithm exhibited excellent training performance with an R^2 score of 0.9767 and maintained good predictive capability on the test dataset, achieving an R^2 value of 0.8913 and a root mean square error (RMSE) of 0.0637.

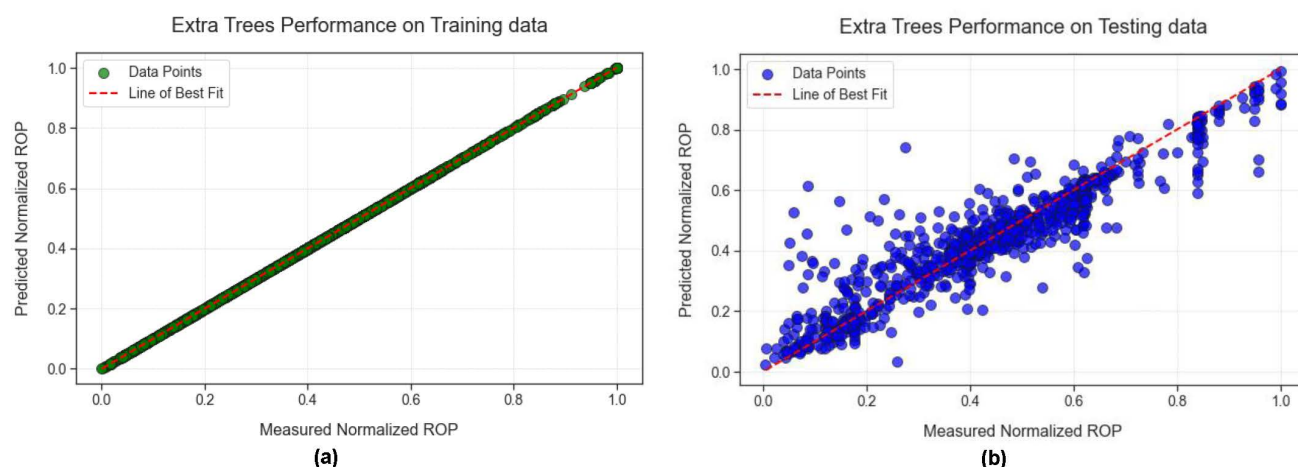
Table 2—Assessment of the proposed ML model performances on training and test sets – Case 1 (using direct drilling parameters)

Model	Training Dataset R ²	Test Dataset R ²	MAE	MSE	RMSE
SVM-R	0.7969	0.7030	0.07	0.0109	0.1043
Random Forest (RF)	0.9804	0.8245	0.05	0.0064	0.0802
Gradient Boosting (GB)	0.9294	0.7890	0.06	0.0077	0.0879
Extra Tree (ET)	1.000	0.8463	0.04	0.0056	0.0751
CatBoost (CB)	0.9855	0.8241	0.05	0.0064	0.0803

Table 3—Assessment of the proposed ML model performances on training and test sets – Case 2 (using DMSE and FET)

Model	Training Dataset R ²	Test Dataset R ²	MAE	MSE	RMSE
SVM-R	0.5913	0.5790	0.10	0.0157	0.1253
Random Forest (RF)	0.9825	0.8727	0.04	0.0047	0.0689
Gradient Boosting (GB)	0.9333	0.8400	0.05	0.0060	0.0773
Extra Tree (ET)	1.0000	0.8802	0.04	0.0045	0.0669
CatBoost (CB)	0.9767	0.8913	0.04	0.0041	0.0637

Regardless of the type of input features, the Extra Trees (ET) algorithm demonstrates superior performance in capturing the complex relationship between ROP values and input variables. To evaluate the best-performing models, cross-validation plots were generated for the ET algorithm using both direct surface drilling parameters and derived controllable variables. The cross-validation plots for both training and test datasets are presented in Figures 6 and 7, illustrating the relationship between measured and predicted normalized ROP values. These plots provide a visual assessment of the ET model's predictive accuracy. The training dataset plot shows that data points align closely with the perfect prediction line, indicating that the ET model was effectively trained. However, a slight discrepancy is observed in the test dataset, as depicted in Figures 6b and 7b. The ET model trained with DMSE and FET achieved an R² of 1.00 on the training dataset and 0.88 on the test dataset, demonstrating strong predictive performance. For further validation, the best-performing ML models from both approaches were used to predict the ROP profile for Well #2. As shown in Figure 8, the proposed ET models successfully forecast the ROP variation with wellbore depth, confirming their reliability and effectiveness in real-world drilling applications.

**Figure 6—Cross-validation plot between measured and predicted normalized ROP developed by Extra Trees Model (using drilling parameters): (a) training database; (b) test database.**

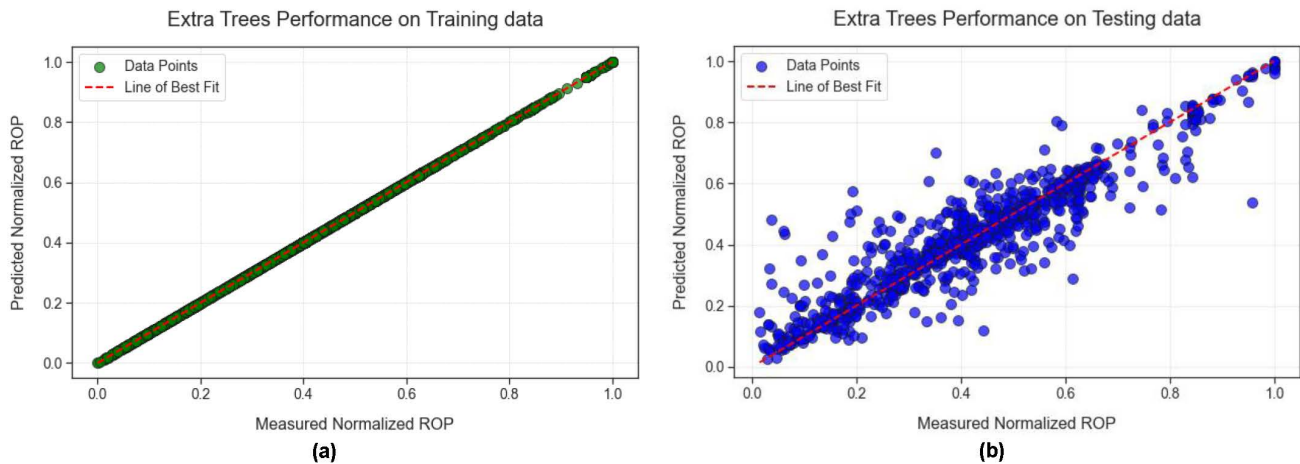


Figure 7—Cross-validation plot between measured and predicted normalized ROP developed by Extra Trees Model (using DMSE and FET): (a) training dataset; (b) test dataset.

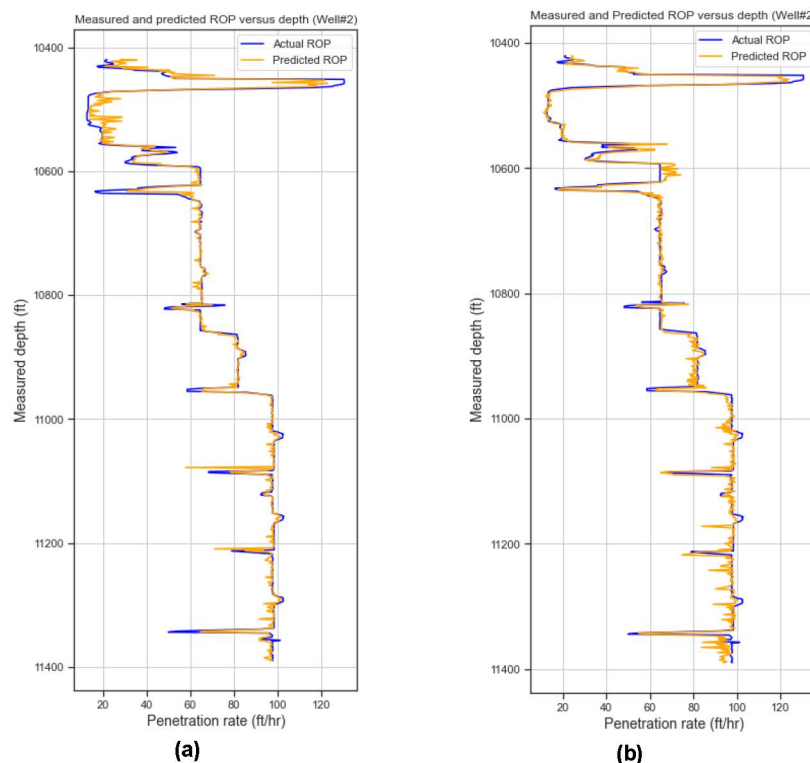


Figure 8—Plots of measured versus predicted ROP using two different modeling approaches: a) real-time drilling parameters and b) controllable derive parameters (DMSE and FET).

Feature importance Analysis

The rate of penetration (ROP) is influenced by various drilling parameters, both controllable and uncontrollable. Previous data-driven modeling studies (Ahmed et al., 2019; Barbosa et al., 2019; Eskandarian et al., 2017) have conducted feature importance analyses to investigate the impact of real-time drilling parameters on ROP. Both Ahmed et al. (2019) and Barbosa et al. (2019) concluded that the most dominant controllable drilling variables, ranked from highest to lowest influence, are weight on bit (WOB), rotational speed (RPM), and mud flow rate, with the uncontrollable variable uniaxial compressive strength (UCS) identified as the fourth most influential factor. Conversely, Eskandarian et al. (2017) found that WOB and mud weight were the two most significant factors affecting ROP. One of the key objectives of this study is to perform a comprehensive feature importance and sensitivity analysis. The ranking of influential

variables differs among the machine learning models used. The results of feature importance experiments from the employed algorithms are presented in Figure 9. As shown in the figure, the CatBoost (CB) model provides a distinct ranking of influential variables compared to the Random Forest (RF) and Gradient Boosting (GB) models. CatBoost highlights torque and UCS as the most influential factors in predicting ROP, while equivalent circulating density (ECD) and mud flow rate have a lower impact. However, the RF and GB models consistently rank pump pressure, torque, UCS, and mud flow rate as the top four influencing factors. Notably, both RF and GB models suggest that WOB has a minimal impact on ROP, a finding that contradicts previous studies (Ahmed et al., 2019; Barbosa et al., 2019; Eskandarian et al., 2017), where WOB was identified as the most dominant variable in the drilling process. The input feature ranking from the CatBoost model suggests that drillers rely on a combination of controllable variables—torque, pump pressure, and WOB—to optimize and regulate ROP.

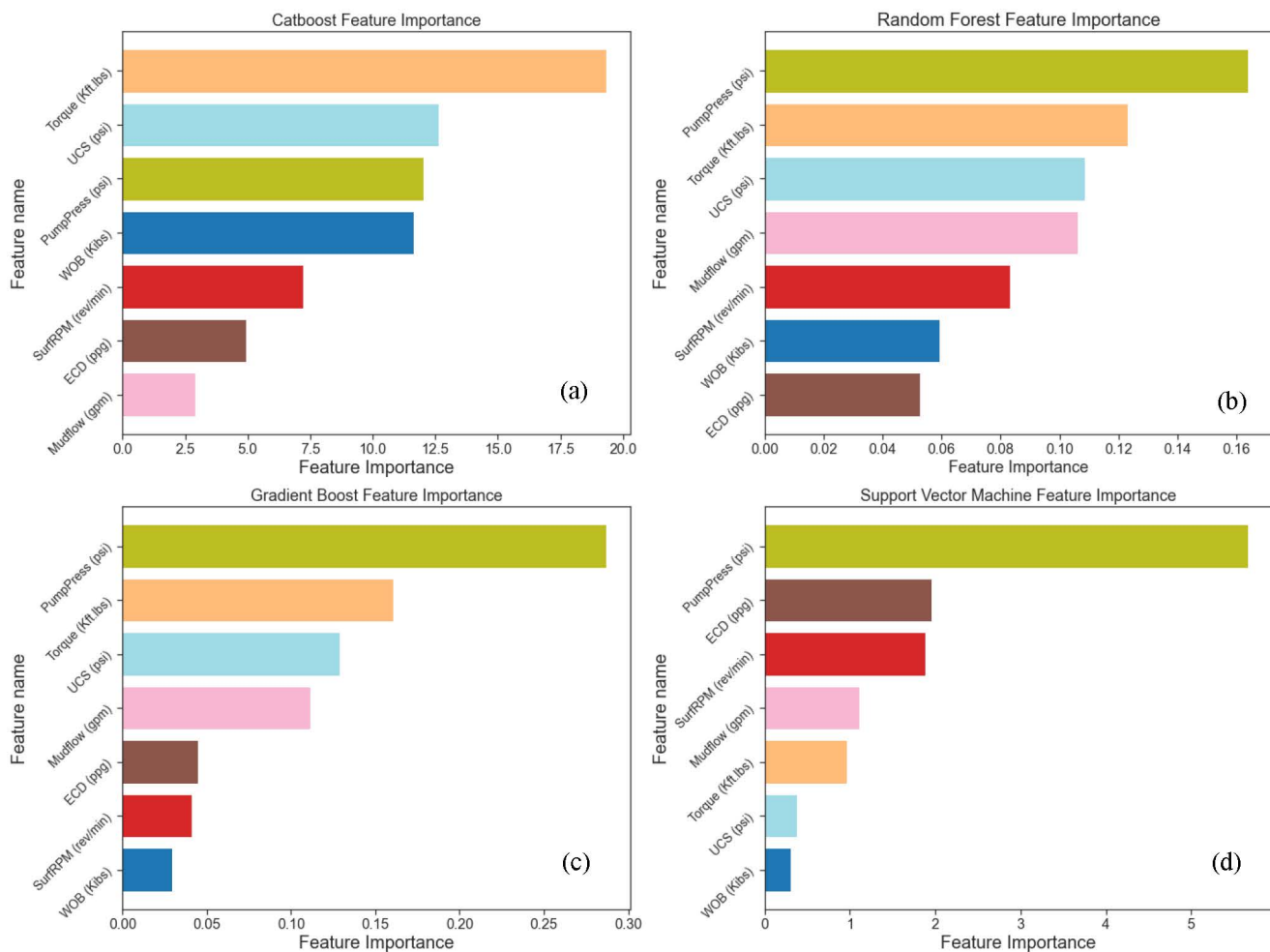


Figure 9—Feature plot ranked by various ML models: (a) Catboost; (b) Random Forest; (c) Gradient Boosting; and (d) support vector machine.

Examination of Model Reliability: ROP prediction for a new drilled well (#6). To assess the robustness and generalization capability of the developed models, the best-performing model from each approach was selected and evaluated against a new wellbore dataset (Well #6), which was not included in the model development process. The comparison results for both models are illustrated in Figure 10. As shown in Figure 10a, the direct surface parameter-based model failed to capture the variation in the ROP trend with depth, instead predicting a relatively constant ROP within the range of 60–75 ft/hr. In contrast, the model based on controllable derived variables exhibited an excellent agreement with the measured

ROP, particularly in complex formation lithology with R^2 and MAE of 0.97 and 0.0465, respectively. The proposed model effectively captured ROP fluctuations with depth, demonstrating its superior predictive capability, as depicted in Figure 10b. This finding reinforces the strong relationship between ROP and the controllable variables, DMSE and FET.

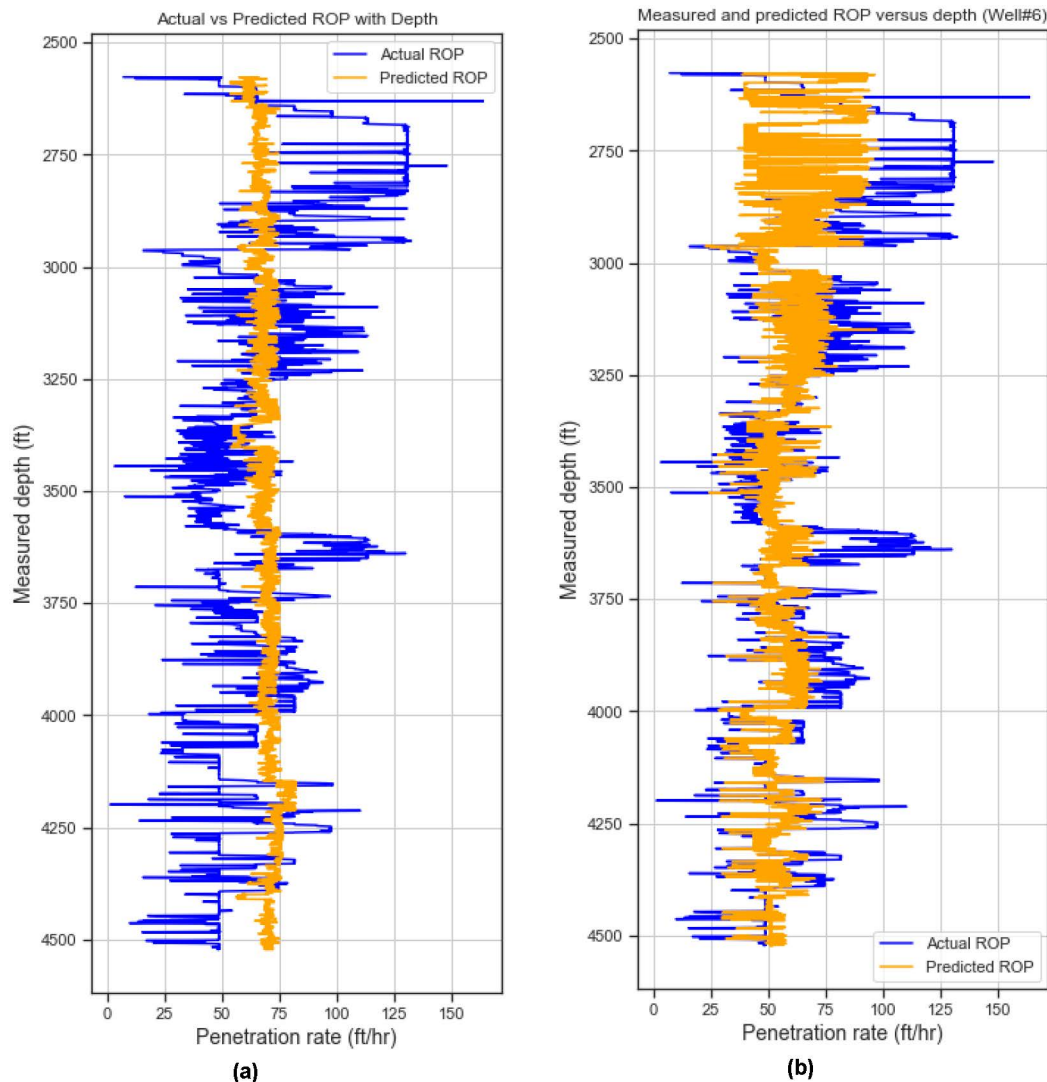


Figure 10—Plots of measured versus predicted ROP for new offset well using two different modeling approaches: a) real-time drilling parameters and b) controllable derive parameters (DMSE and FET).

Conclusions

In this study, a key parameter for assessing drilling efficiency was investigated using artificial intelligence techniques. Approximately 6,279 data points, including mechanical drilling parameters and logging-while-drilling (LWD) measurements, were gathered from five wells in the Volve field. This dataset, representing actual drilling operations, was used to develop the ROP model. The model development followed two distinct approaches: one utilizing real-time recorded drilling parameters as input features and the other incorporating derived controllable parameters, specifically drilling mechanical specific energy (DMSE) and feed thrust force (FET). Unlike previous studies, this research employed five supervised regression machine learning algorithms to model the rate of penetration (ROP). To validate the model's strength, the best-performing machine learning model was tested on an offset well (Well #6), which was not involved

in the initial model training and testing procedure. Based on the study findings, the following conclusions can be drawn:

- A novel and reliable model has been developed to accurately predict the drilling rate of penetration based on controllable derived variables such as drilling mechanical specific energy (DMSE) and feed thrust force (FET).
- The study results confirm the hypothesis that using controllable derived variables as input features enhances the performance and generalization of the ROP model, providing greater accuracy compared to direct surface drilling variables.
- Regardless of the selected input variables, whether real-time surface drilling parameters or derived controllable variables, the Extra Trees (ET) model predicts ROP with 100% accuracy on the training dataset and an R^2 of 88% on the test dataset.
- The model assessment disclosed that the ML models can be ranked based on the accuracy namely as Extra Trees, CatBoost, Random Forest, and Gradient Boosting algorithm.
- The relative feature importance analysis ranked the input variables in order of influence, from most to least dominant: surface torque, uniaxial confining strength (UCS), pump pressure, weight on bit, surface rotational speed, equivalent circulating density, and mud flow rate.
- The best-performing ML model, utilizing DMSE and FET as input variables, delivers highly accurate ROP predictions for the new offset well, outperforming the model based on real-time surface drilling parameters. The conventional data-driven ROP model, which relies solely on surface drilling parameters, struggled to capture ROP variations with depth, limiting its generalization capability.
- The new data-driven ROP model, incorporating DMSE and FET, can be integrated with various mathematical optimization techniques to optimize drilling parameters, enhance efficiency, and ultimately lower overall drilling costs.

Acknowledgements

The authors express their gratitude to Australian University-Kuwait (AU) and the Project-Based Learning (PBL) team for their invaluable support and resources, which significantly contributed to the successful completion of this work. Additionally, they extend their appreciation to the University of Oklahoma (OU) for its collaboration and support.

References

- Amadi, K., Iyalla, I., Prabhu, R., Alsaba, M. and Waly, M., 2023a. Development of predictive optimization model for autonomous rotary drilling system using machine learning approach. *Journal of petroleum exploration and production technology*, **13**(10), pp.2049–2062.
- Ahmed, O., Adeniran, A. and Samsuri, A., 2018. Rate of penetration prediction utilizing hydromechanical specific energy. *Drilling*, pp.105–131.
- Ahmed, O.S., Adeniran, A.A. and Samsuri, A., 2019. Computational intelligence-based prediction of drilling rate of penetration: A comparative study. *Journal of Petroleum Science and Engineering*, **172**, pp.1–12.
- Amadi, K.W., Alsaba, M.T., Iyalla, I., Prabhu, R. and Elgaddafi, R.M., 2023b, July. Machine Learning Techniques for Real-Time Prediction of Essential Rock Properties Whilst Drilling. In SPE Nigeria Annual International Conference and Exhibition (p. D031S017R004). SPE.
- Arabjamaloei, R. and Shadizadeh, S., 2011. Modeling and optimizing rate of penetration using intelligent systems in an Iranian southern oil field (ahwaz oil field). *Petroleum Science and Technology*, **29**(16), pp.1637–1648.
- Amadi, K. and Iyalla, I., 2012, June. Application of mechanical specific energy techniques in reducing drilling cost in deepwater development. In SPE deepwater drilling and completions conference (pp. SPE-156370). SPE.
- Anemangely, M., Ramezanzadeh, A. and Behboud, M.M., 2019. Geomechanical parameter estimation from mechanical specific energy using artificial intelligence. *Journal of Petroleum Science and Engineering*, **175**, pp.407–429.

- Hareland, G. and Rampersad, P.R., 1994, April. Drag-bit model including wear. In SPE Latin America and Caribbean Petroleum Engineering Conference (pp. SPE-26957). SPE.
- Hammoutene, C. and Bits, S., 2012, February. FEA modelled MSE/UCS values optimise PDC design for entire hole section. In SPE North Africa Technical Conference and Exhibition (pp. SPE-149372). SPE.
- Jiang, W. and Samuel, R., 2016, March. Optimization of rate of penetration in a convoluted drilling framework using ant colony optimization. In SPE/IADC Drilling Conference and Exhibition (p. D031S026R006). SPE.
- Khalilidermani, M. and Knez, D., 2023. A Survey on the Shortcomings of the Current Rate of Penetration Predictive Models in Petroleum Engineering. *Energies*, **16**(11), p.4289.
- Khalilidermani, M. and Knez, D., 2022. A Survey of Application of Mechanical Specific Energy in Petroleum and Space Drilling. *Energies*, **15** (9), 3162.
- Khoukhi, A. and AlArfaj, I., 2012, October. Rate of Penetration Prediction and Optimization using Advances in Artificial Neural Networks, a Comparative Study. In *IJCCI* (pp. 647–652).
- Lindqvist, P.A., 1982. Rock fragmentation by indentation and disc cutting: some theoretical and experimental studies (Doctoral dissertation, Luleå tekniska universitet).
- Liang, H., Chen, H., Guo, J., Bai, J. and Jiang, Y., 2022. Research on lithology identification method based on mechanical specific energy principle and machine learning theory. *Expert Systems with Applications*, **189**, p.116142.
- Li, W., Zhao, X., Li, Y., Ji, Y., Peng, H., Liu, L. and Yang, Q., 2015. Laboratory investigations on the effects of surfactants on rate of penetration in rotary diamond drilling. *Journal of Petroleum Science and Engineering*, **134**, pp.114–122.
- Mantegazini, D.Z., Nascimento, A., Dornelas, V.F. and Mathias, M.H., 2024. Analysis and Multi-Objective Optimization of the Rate of Penetration and Mechanical Specific Energy: A Case Study Applied to a Carbonate Hard Rock Reservoir Based on a Drill Rate Test Using Play-Back Methodology. *Applied Sciences*, **14**(6), p.2234.
- Moraveji, M.K. and Naderi, M., 2016. Drilling rate of penetration prediction and optimization using response surface methodology and bat algorithm. *Journal of Natural Gas Science and Engineering*, **31**, pp.829–841.
- Maurer, W.C., 1962. The perfect cleaning theory of rotary drilling. *Journal of Petroleum Technology*, **14**(11), pp.1270–1274.
- Oyler, D.C., Mark, C. and Molinda, G.M., 2010. In situ estimation of roof rock strength using sonic logging. *International Journal of Coal Geology*, **83**(4), pp.484–490.
- Motahhari, H.R., Hareland, G. and James, J.A., 2010. Improved drilling efficiency technique using integrated PDM and PDC bit parameters. *Journal of Canadian Petroleum Technology*, **49**(10), pp.45–52.
- Mohan, K., Adil, F. and Samuel, R., 2009, March. Tracking drilling efficiency using hydro-mechanical specific energy. In SPE/IADC Drilling Conference and Exhibition (pp. SPE-119421). SPE.
- Mohan, K., Adil, F. and Samuel, R., 2015. Comprehensive hydromechanical specific energy calculation for drilling efficiency. *Journal of Energy Resources Technology*, **137**(1), p.012904.
- Paone, J., Bruce, W. E., Virgilio, P. R. Drilling Studies: Statistical Regression Analysis of Diamond Drilling. US Dept. of the Interior, Bureau of Mines (1966).
- Pacis, F.J., Ambrus, A., Alyaev, S., Khosravian, R., Kristiansen, T.G. and Wiktorski, T., 2023. Improving predictive models for rate of penetration in real drilling operations through transfer learning. *Journal of Computational Science*, **72**, p.102100.
- Robinson, L. H., & Ramsey, M. S. (2001). Are You Drilling Optimized or Spinning Your Wheels? AADE 2001 National Drilling Conference, "Drilling Technology - The Next 100 Years", (AADE 01-NC-HO-31), 1–11.
- Riazi, M., Mehrjoo, H., Nakhaei, R., Jalalifar, H., Shateri, M., Riazi, M., Ostadhassan, M. and Hemmati-Sarapardeh, A., 2022. Modelling rate of penetration in drilling operations using RBF, MLP, LSSVM, and DT models. *Scientific Reports*, **12**(1), p.11650.
- Rushd, S., Hafsa, N., Al-Faiad, M. and Arifuzzaman, M., 2021. Modeling the settling velocity of a sphere in Newtonian and non-Newtonian fluids with machine-learning algorithms. *Symmetry*, **13**(1), p.71.
- Reza, M.R. and Alcocer, C.F., 1986, April. A unique computer simulation model well drilling: part I—the Reza drilling model. In SPE Western Regional Meeting (pp. SPE-15108). SPE.
- Sinkala, T. 1989 "Hole deviatons in percussion drilling and control measures", Ph. D. dissertation, Lulea Univ. Technol., Lulea, Sweden.
- Soares, C. and Gray, K., 2019. Real-time predictive capabilities of analytical and machine learning rate of penetration (ROP) models. *Journal of Petroleum Science and Engineering*, **172**, pp.934–959.
- Teale, R., 1965, March. The concept of specific energy in rock drilling. In *International journal of rock mechanics and mining sciences & geomechanics abstracts* (Vol. 2, No. 1, pp. 57–73). Pergamon.
- Warren, T.M., 1984. Factors affecting torque for a roller cone bit. *Journal of petroleum technology*, **36**(09), pp.1500–1508.
- Warren, T.M., 1981. Drilling model for soft-formation bits. *Journal of Petroleum Technology*, **33**(06), pp.963–970.