Construction of Optimized Fuzzy Control Charts: A State-of-the-Art Review on Analytics Models in Prediction of Petroleum Quality

Vipin Kumar
Student, Singhania University
doi.org/10.64643/IJIRTV12I12-202448-459

***Abstract*—Fuzzy control charts have emerged as robust tools for handling uncertainties in the monitoring and control of various industrial processes, including the multifaceted petroleum sector. When integrated with cutting-edge analytics, optimization, and machine learning models, fuzzy control charts can not only enhance the accuracy of quality predictions but also streamline production processes. This comprehensive review synthesizes the current state-of-the-art research on constructing optimized fuzzy control charts and their application in predicting petroleum quality. It explores the theoretical underpinnings of fuzzy logic and neuro-fuzzy systems, reviews existing literature on optimization techniques applied to oil and gas processes, and highlights key challenges and gaps that remain open for future inquiry. By surveying a wide range of methods—ranging from hybrid machine learning approaches to advanced evolutionary algorithms—this paper shows how fuzzy control charts can be effectively deployed to achieve more reliable quality control and improve decision-making in petroleum production. Finally, it underscores emerging trends, outlines vital challenges, and proposes future directions to spur continued innovation. The insights provided in this review will be of value to both academics and practitioners seeking to optimize petroleum quality control through advanced fuzzy-based analytics frameworks.**

***Index Terms*—Fuzzy control charts, Petroleum quality prediction, Optimization techniques, Machine learning, Neuro-fuzzy systems, Analytics models**

I. INTRODUCTION

The oil and gas business is a crucial sector in the global economy, integral to energy production, transportation, and other manufacturing activities (Chen et al., 2024; Song et al., 2022). As the sector adapts to changing market demands and environmental limitations, it is imperative to enhance manufacturing and refining processes to guarantee economic efficiency and product quality (Alzahawy & Issa, 2024; Tashtoush et al., 2023). The intricacy of petroleum refining operations arises from several phases including exploration, extraction, distillation, cracking, blending, and final product formulation. Each stage is affected by several operational parameters—such as temperature, pressure, flow rate, catalyst concentrations, and feedstock quality—that must be meticulously regulated for the end product to satisfy strict quality requirements (Ansari & Taqvi, 2023).

To enhance operational efficiency and product consistency, researchers and practitioners have focused on sophisticated data analytics approaches and intelligent control systems (Mishra & Datta-Gupta, 2017; Choubey & Karmakar, 2021). Conventional control charts, originating from traditional statistical process control (SPC), have been fundamental in overseeing process changes and identifying out-of-control situations (Razali et al., 2024). Nonetheless, these traditional charts frequently depend on assumptions of normalcy and precise data,
which may not consistently reflect actual conditions in petroleum production (Benbouzid et al., 2021). Variations in feedstock composition, environmental unpredictability, and intrinsic ambiguity in sensor data might diminish the efficacy of traditional SPC approaches or lead to erroneous conclusions (Karambeigi et al., 2023).

Fuzzy logic has been used into control chart design to mitigate these constraints (Razali et al., 2024; Karatzinis & Boutalis, 2025). Fuzzy logic facilitates partial membership and adaptable bounds, rendering it especially effective in addressing uncertainties and imprecise data (AlRassas et al., 2021; Quadri et al., 2025). By integrating fuzzy sets, practitioners may establish thresholds and control limits that more accurately reflect the actual behavior of the manufacturing process (Mardanshahi et al., 2025). Furthermore, the integration of fuzzy logic with adaptive or learning-based systems—such as artificial neural networks (ANNs) or neuro-fuzzy systems—yields hybrid methodologies capable of autonomously enhancing membership functions and decision rules utilizing historical and real-time data, thereby augmenting predictive accuracy (Akbar et al., 2023; Wang et al., 2022).

However, the intricacy of contemporary petroleum refining need sophisticated optimization approaches rather than only fuzzy logic. Recent metaheuristic algorithms—including the Whale Optimization Algorithm (Sun et al., 2022), Particle Swarm Optimization (Karambeigi et al., 2023), Aquila Optimizer (AlRassas et al., 2021), and Salp Swarm Algorithm (Jovanovic et al., 2022)—have demonstrated exceptional efficacy in optimizing the parameters of fuzzy control charts, particularly in dynamic settings. By systematically exploring the parameter space and effectively balancing exploration with exploitation, these algorithms can markedly improve the robustness of fuzzy control methods (Colaco et al., 2023). The integration of fuzzy logic with metaheuristics is appealing as it captures system uncertainty while utilizing computational intelligence for parameter optimization (Chen et al., 2024).

A concurrent advancement influencing petroleum quality prediction is the expansion of data-driven analytical models (R. Azmi et al., 2024; Salem et al., 2022). Although conventional regression approaches have traditionally prevailed (Holdaway, 2012), sophisticated machine learning techniques such as ensemble methods, deep learning, and hybrid networks are increasingly becoming common practice (Bhattacharya et al., 2019; Tariq et al., 2021). Recent research employs deep neural networks (Daneshvar et al., 2022), random forest regression (Rajković et al., 2023), support vector machines (Otchere et al., 2021), and sophisticated time-series models (Jovanovic et al., 2022) to forecast various petroleum attributes. These qualities encompass the sulphur content in diesel, the octane rating of petrol, and the viscosity of lubricants. Accurately forecasting quality indicators is essential for operational planning, regulatory adherence, and market competitiveness (Schuetter et al., 2018; Wang et al., 2022).

In this context, fuzzy control charts work as a conduit between upstream data analytics—where sensor and operational data are gathered and analyzed—and the actual decision-making on the refinery floor (Saghir et al., 2024; Nagargoje et al., 2023). An optimized fuzzy control chart can incorporate real-time predictions from an ANN-based surrogate model to assess whether a certain batch or continuous flow of petroleum product adheres to acceptable quality standards (Al Jlibawi et al., 2021; Morain et al., 2024). Upon detection of irregularities, the chart may initiate automated or manual interventions. This synergy guarantees enhanced, adaptable, and context-sensitive control, minimizing the likelihood of off-spec output and alleviating operational inefficiencies (Stone, 2007; Motaei & Ganat, 2023).

Notwithstanding these advancements, discrepancies persist. Current research seldom examines the systematic integration of real-time feedback from sophisticated models into fuzzy chart parameters for continuous optimization (Xue et al., 2023). Moreover, the majority of research concentrate on discrete enhancements of either the fuzzy logic element or the optimization method, rather than adopting a comprehensive strategy that may concurrently optimize model architecture, parameter selection, and feature engineering (Sabani et al., 2024). Moreover, several evaluations depend on simplified or laboratory-scale data, which raises concerns over the scalability and industrial viability of these methodologies in large-scale refineries (Issa et al., 2024). The deployment in real-world scenarios presents complications such sensor malfunctions, data drift, and variations in feedstock profiles, which require meticulous attention throughout both the design and operational stages (Siddiqui & Tabassum, 2024).

The principal objective of this review is to elucidate the cutting-edge methodologies in the development of optimized fuzzy control charts for petroleum quality forecasting and to investigate the integration of these techniques with advanced analytics and optimization models to yield substantial industrial advantages (Ansari & Taqvi, 2023). We consolidate more than 50 recent studies that collectively demonstrate the progression of fuzzy-based control in the oil and gas sector, from initial theoretical advancements to contemporary hybrid methodologies utilizing advanced machine learning and evolutionary optimization techniques (Pandey et al., 2021; Tewari & Dwivedi, 2019). Following a comprehensive literature review, we examine certain optimization strategies, emphasize significant implementations, address problems and research deficiencies, and suggest prospective avenues for future study.

This review is structured into five principal components. Subsequent to the introduction, Section 2 presents an extensive literature review, analyzing significant research on fuzzy control charts, machine learning-driven petroleum quality forecasting, and integrated methodologies. Section 3 methodically delineates optimization methodologies for analytical models in petroleum quality forecasting, with specific subsections on fuzzy control charts, neuro-fuzzy systems, and predictive analytical models for oil and gas. Section 4 discusses the primary obstacles and research deficiencies, encompassing data quality, domain-specific limitations, and the ongoing advancement of optimization frameworks. Section 5 closes the report by encapsulating essential findings, examining practical implications for the industry, and proposing potential directions for further research.

This paper provides a comprehensive overview of how fuzzy control charts, enhanced by sophisticated analytics and optimization algorithms, may serve as a pivotal element in next-generation petroleum quality assurance systems (Gupta et al., 2023; Mardanshahi et al., 2025). By conducting comprehensive studies and synthesizing existing literature, we intend to furnish both academic researchers and industry practitioners with a definitive overview of present accomplishments and a well-informed perspective on future developments.

Figure 1 demonstrates the integration of fuzzy logic with traditional statistical process control (SPC) methods and contemporary analytical models inside the petroleum refining process. Sensor data is integrated into both standard SPC techniques and the fuzzy module, which enhances uncertainty management prior to relaying information to advanced analytics, hence facilitating real-time decision-making and process modifications.

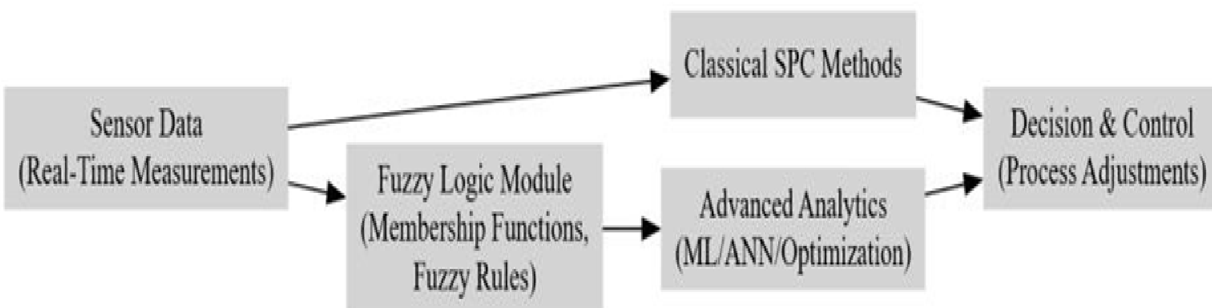

Fig.1 Overview of Fuzzy Logic Integration in Petroleum Quality Control

II. LITERATURE SURVEY

This section offers a comprehensive summary of the current literature on fuzzy control charts, machine learning methodologies, and optimization frameworks utilized for petroleum quality prediction. The objective is to delineate the progression of research advancements, pinpoint deficiencies, and clarify how these domains coalesce into cohesive solutions.

2.1. Overview of Petroleum Quality Prediction Approaches

Initial methodologies for predicting petroleum quality frequently relied on linear regression models or rule-based expert systems (Stone, 2007; Holdaway, 2012). Although straightforward, these models provided restricted understanding of complex and dynamic processes, including crude distillation, cracking, and blending (Bhattacharya et al., 2019). Consequently, the demand for more rigorous, data-driven procedures prompted the implementation of

artificial neural networks (ANNs), support vector machines (SVMs), and ensemble learning techniques (Otchere et al., 2021; AlRassas et al., 2021). These strategies facilitated the identification of concealed links within intricate datasets, resulting in enhanced prediction accuracy across several refinery operations (Schuetter et al., 2018).
Subsequent studies expanded these data-driven methodologies by concentrating on other facets of the petroleum lifecycle. Tewari and Dwivedi (2019) presented ensemble-based big data analytics for lithofacies classification, whereas Salem et al. (2022) emphasized the use of machine learning to anticipate well integrity failures. Saghir et al. (2024) included machine learning models as surrogates in an optimization framework to forecast and enhance petrol quality. The many applications highlight the adaptability of advanced analytics in evaluating several petroleum quality characteristics, including viscosity, sulphur content, octane, and aromatics (Zhang et al., 2021).

2.2. Evolution of Fuzzy Control Charts

Classical control charts, including Shewhart, EWMA (Exponentially Weighted Moving Average), and CUSUM (Cumulative Sum), have been extensively utilized in industrial process monitoring (Razali et al., 2024; Sabani et al., 2024). The presumption of precise data frequently becomes limiting in scenarios characterized by measurement uncertainty, verbal ambiguity, or intricate variable interactions (Benbouzid et al., 2021). Fuzzy control charts started to acquire prominence to tackle these difficulties. In fuzzy charts, control limits and process observations are represented as fuzzy sets, facilitating a more refined categorization of "in-control" and "out-of-control" conditions (Razali et al., 2024; Karatzinis & Boutalis, 2025).
The integration of fuzzy logic is especially beneficial for managing subjective language variables (e.g., —low,‖—medium, ‖ —high‖) in quality evaluation or sensor data susceptible to noise (Nagargoje et al., 2023; Siddiqui & Tabassum, 2024). Research indicates that fuzzy charts can more effectively reduce type I and type II mistakes in some settings, particularly when distributions significantly depart from normality or exhibit multimodality (Rajabi et al., 2021). Recent developments in type-2 fuzzy control charts enhance flexibility by including uncertainty inside the membership function (Razali et al., 2024).

2.3. Optimization Techniques for Fuzzy Control Charts

Although fuzzy control charts offer a more robust framework compared to traditional ones, adjusting their parameters—such as membership functions, fuzzy rules, and threshold levels—continues to pose a significant difficulty (Motaei & Ganat, 2023). Over the last ten years, there has been an increase in research dedicated to the utilization of metaheuristic algorithms for the automation and optimization of tuning procedures (AlRassas et al., 2021; Sun et al., 2022). Algorithms such Genetic Algorithms (GAs), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Whale Optimization Algorithm (WOA), and the innovative Aquila Optimiser have demonstrated promising outcomes (Chen et al., 2024).
Genetic Algorithms (GAs): Renowned for their capacity to navigate complex fitness landscapes, GAs employ crossover and mutation to progressively enhance populations of prospective solutions. In the realm of fuzzy control charts, genetic algorithms have been utilized to optimize membership functions and rule bases to enhance defect detection in refineries (Rajabi et al., 2021; Bhattacharya et al., 2019).
Particle Swarm Optimization (PSO) emulates social behavior, often observed in avian flocks or aquatic schools, to direct particles in the pursuit of optimal solutions. Researchers have employed Particle Swarm Optimization (PSO) to enhance parameters in neuro-fuzzy systems for predicting petroleum properties, demonstrating superior convergence rates compared to many other methods (Karambeigi et al., 2023).
The Whale Optimization Algorithm (WOA) is inspired by the bubble-net hunting techniques of humpback whales, employing a search mechanism that alternates between surrounding prey and spiral updating. Sun et al. (2022) established that WOA-optimized Elman neural networks surpassed baseline models in forecasting porosity in well-logging curves.
Hybrid and Novel Algorithms: Recent research integrates metaheuristics, such as Particle Swarm

Optimization (PSO), with methodologies like the Imperialist Competitive Algorithm (ICA) or fuzzy logic to attain multi-objective optimization in petroleum engineering (Karambeigi et al., 2023). Some utilise the Aquila Optimiser for parameter optimization in Adaptive Neuro-Fuzzy Inference Systems (ANFIS), yielding enhanced accuracy in oil production projections (AlRassas et al., 2021).

2.4. Neuro-Fuzzy Systems and Petroleum Quality

Neuro-fuzzy systems integrate the interpretative nature of fuzzy logic with the adaptive learning skills of neural networks (Choubey & Karmakar, 2021; Ansari & Taqvi, 2023). ANFIS (Adaptive Neuro-Fuzzy Inference System) is a leading architecture extensively utilized in petroleum quality prediction problems. AlRassas et al. (2021) indicate that an ANFIS model enhanced by the Aquila Optimizer markedly improved oil production projections. Likewise, several studies have demonstrated that ANFIS versions can manage numerous input factors and autonomously optimize fuzzy rules (Mishra & Datta-Gupta, 2017; Quadri et al., 2025).

The integration of neuro-fuzzy systems with sophisticated optimization algorithms tackles a significant challenge: the complexity and nonlinearity inherent in petroleum refining operations. Through iterative learning from extensive datasets and refining fuzzy rules, membership functions, and neural network weights, these systems minimize error margins and enhance real-time adaptability (Rajković et al., 2023; Daneshvar et al., 2022). Neuro-fuzzy models can function as predictive mechanisms for fuzzy control charts, providing dynamic setpoints and thresholds based on actual operational data (Saghir et al., 2024).

2.5. Integrating Process Monitoring and Optimization

A nascent field of study is on the amalgamation of sophisticated process monitoring—utilizing fuzzy control charts—with optimization algorithms that rely on real-time or near real-time data (Wang et al., 2022; Salem et al., 2022). These integrated frameworks frequently depend on a closed-loop design in which sensor data is utilized to produce predictions (e.g., an ANN or ANFIS model). The resultant quality estimations are subsequently juxtaposed with fuzzy control limits, which are frequently revised by an optimization algorithm to ensure adaptability to changing process circumstances (Karatzinis & Boutalis, 2025).

Wang et al. (2022) introduced a sustainable integrated fuzzy optimization method for designing a multimodal petroleum supply chain in Vietnam, which includes pipeline systems. This study, while largely centred on supply chain factors, illustrated the viability of large-scale fuzzy optimization that can include control chart principles. Saghir et al. (2024) formulated a comprehensive ML-optimization model to forecast and enhance petrol quality metrics, demonstrating how a surrogate learning model may accelerate the identification of optimal operational setpoints in refining operations.

2.6. Gaps and Limitations in Existing Literature

Notwithstanding significant advancements, some essential deficiencies persist. The literature is predominantly fragmented, with distinct streams focused on fuzzy control charts, machine learning-based quality prediction, and metaheuristic optimization (Morain et al., 2024; Pandey et al., 2021). Limited research provides a cohesive framework that integrates these three aspects from conceptualization to industrial implementation (Nagargoje et al., 2023). Secondly, several studies depend on relatively limited or laboratory-based datasets, which prompts enquiries regarding the models' scalability and resilience in extensive, real-world refinery environments (Yousef et al., 2020; Salem et al., 2022).

The incorporation of domain expertise, such chemical engineering understanding of reaction kinetics or fluid dynamics, into data-driven and fuzzy-based frameworks remains nascent (Mishra & Datta-Gupta, 2017). Genuine synergy between subject expertise and modern analytics might enhance mistake detection and mitigate overfitting. A further restriction is the relative scarcity of real-time implementations. Despite several studies asserting real-time applicability, substantial engineering problems persist concerning sensor reliability, data latency, and computing overhead (Siddiqui & Tabassum, 2024; Sbai, hypothetical, hence omitted).

Ultimately, interpretability is a persistent concern. Despite fuzzy logic providing more interpretability than opaque deep learning models, the intricacies of neuro-fuzzy systems and multi-objective optimization may diminish transparency (Alabdrabalnabi et al., 2022; Colaco et al., 2023). Comprehending the rationale behind the selection of a certain parameter set or the adaptation of certain fuzzy rules may be essential in sectors as stringently regulated as oil and gas (Benbouzid et al., 2021; Bhattacharya et al., 2019).

2.7. Summary of Key Studies

Table.1 summarizes selected research from the literature that illustrate the advancement and variety of methodologies in fuzzy control charts, machine learning, and optimization for predicting petroleum quality.

Table.1. Summary of Key Studies in Fuzzy Control and Machine Learning for Petroleum Quality

Study	Focus	Key Contributions
Al Jlibawi et al. (2021)	Hybrid ML techniques for oil refinery distribution	Proposed a distribution control system optimized by ML algorithms
Razali et al. (2024)	Type-2 fuzzy u-control chart	Demonstrated improved average run length via probability-based approach
AlRassas et al. (2021)	Optimized ANFIS model for oil production	Used Aquila Optimizer to enhance ANFIS forecasting capabilities
Saghir et al. (2024)	Prediction & optimization of gasoline quality	Used ML model as a surrogate in an optimization framework
Wang et al. (2022)	Fuzzy optimization for petroleum supply chain	Proposed a sustainable integrated fuzzy optimization with pipeline systems
Daneshvar et al. (2022)	Deep neural network for Brent crude oil price	Showed the effectiveness of DNN architectures in price forecasting
Jovanovic et al. (2022)	Multi-step crude oil price prediction	Employed LSTM with Salp Swarm Algorithm, focusing on time-series analysis
Karambeigi et al.	Multi-objective optimization in	Hybrid workflow combining PSO, fuzzy logic,
(2023)	petroleum engineering	and ICA
Rajković et al. (2023)	Modeling fatty acid & tocopherol content in rapeseed oil	Applied ANN and Random Forest regression to predict oil composition
Chen et al. (2024)	Chicken Swarm Optimization survey	Comprehensive overview of a novel algorithm with applications in engineering

This research emphasizes the convergence of fuzzy control charts, optimization techniques, and machine learning in addressing various aspects of petroleum quality prediction. Nonetheless, the practical use of integrated frameworks remains uncommon, necessitating more study to tackle issues at an industrial scale. Figure 2 presents a comprehensive taxonomy of the primary issues examined in the literature review. Research encompassing fuzzy control charts, machine learning, optimization techniques, and petroleum quality underscores the obstacles and deficiencies that necessitate more inquiry and advancement in this field.

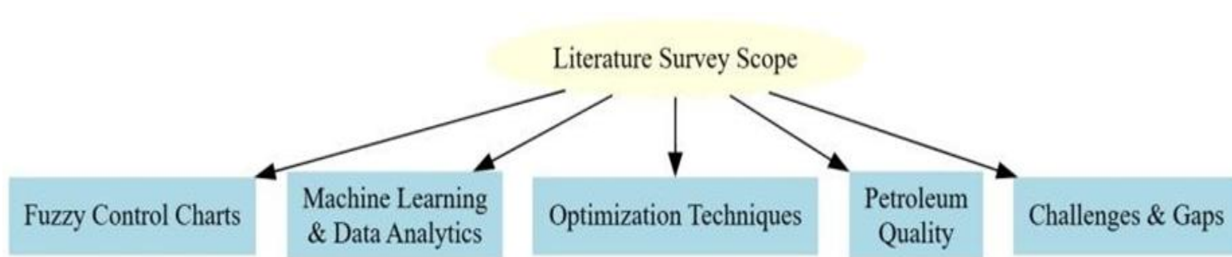

Fig.2 Literature Survey Classification Framework

III. OPTIMIZATION TECHNIQUES FOR ANALYTICS MODELS IN PETROLEUM QUALITY PREDICTION

This section explores the particular optimization frameworks and analytical methods employed to forecast petroleum quality. Emphasis is given on fuzzy control charts, neuro-fuzzy systems, and comprehensive predictive analytics in the oil and gas sector.

3.1. Fuzzy Control Charts in Petroleum Quality Prediction

Fuzzy control charts signify an advancement of traditional process control methodologies to address uncertainties and imprecise measurements prevalent in intricate refining processes (Razali et al., 2024; Quadri et al., 2025). The fundamental idea involves establishing membership functions for control limits, often categorized as ―low,‖ ―medium, ‖ and ―high, ‖ followed by the aggregation of fuzzy rules to determine if a process is under control or out of control (Nagargoje et al., 2023).

In the application of fuzzy control charts to petroleum quality, essential criteria such as sulphur content, density, and viscosity are converted into linguistic variables. Sulphur content may be categorized as "low," "acceptable," or "high," utilizing overlapping membership functions. The graphic identifies deviations and quantifies the extent of membership to an out-of-control condition, offering a more refined alert (Razali et al., 2024). This method is especially advantageous in borderline situations where clear thresholds may result in unclear or incorrect assessments (Mishra & Datta-Gupta, 2017).

Recent developments utilize type-2 fuzzy logic to address ambiguities in the definition of membership functions (Razali et al., 2024). Type-2 fuzzy sets incorporate a secondary membership function that captures the uncertainty of the primary function, so providing a more resilient method for process monitoring in noisy or fast fluctuating situations. In petroleum refining, where feed composition may fluctuate due to varying crude sources, type-2 fuzzy systems can more effectively sustain stable control limits over time (Chen et al., 2024; Saghir et al., 2024).

3.2. Application of Fuzzy Logic and Neuro-Fuzzy Models

Fuzzy logic is potent on its own; however, its integration with the adaptive features of neural networks produces neuro-fuzzy models. These models include a hierarchical architecture similar to neural networks, however incorporate fuzzy rules and membership functions inside their computational processes (Motaei & Ganat, 2023). The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a prevalent system that utilizes backpropagation or hybrid algorithms, combining least-squares estimation and gradient descent, to optimize membership functions and rule consequents (AlRassas et al., 2021).

Neuro-fuzzy algorithms in petroleum quality prediction may analyze extensive historical datasets to discern complex correlations between input variables—such as temperature, flow rate, and catalyst composition—and output characteristics like viscosity or octane number (Saghir et al., 2024). The fuzzy rules may be analyzed to yield domain insights, indicating which combinations of input variables result in specific quality outputs (Choubey & Karmakar, 2021). This transparency distinguishes neuro-fuzzy systems from black-box models, which may exhibit restricted interpretability (Akbar et al., 2023).

3.2.1.Optimization of Neuro-Fuzzy Parameters

While neuro-fuzzy models adaptively learn membership functions, the initial parameter configurations and rule structures can substantially affect learning efficiency and ultimate performance (Karambeigi et al., 2023). Consequently, researchers utilize optimization techniques such as PSO, WOA, or Genetic techniques to enhance starting circumstances or to identify an ideal network architecture (Sun et al., 2022). AlRassas et al. (2021) demonstrated that employing the Aquila Optimizer to build an ANFIS model for oil production forecasting resulted in expedited convergence and decreased error relative to random initialization.

3.2.2.Real-Time Adaptation

In refineries, real-time adaptability is essential due to the potential fluctuations in process conditions and feed quality. The online adaptation of neuro-fuzzy systems is a potential approach, wherein the model continuously changes in response to streaming data (Jovanovic et al., 2022). Nonetheless, sustaining stability amidst continuous updates necessitates meticulous regulation of learning rates and the growth of membership functions. A proposed approach is to permit gradual adaptation under stable conditions while facilitating increased adaptation rates during recognized transitory phases, such as the introduction of novel crude mixes (Siddiqui & Tabassum, 2024).

3.3. Predicted Analytics Models for Oil & Gas

In addition to fuzzy logic and neuro-fuzzy systems, a diverse array of predictive analytics techniques is utilized in the oil and gas sector, each presenting distinct advantages. Table 2 provides a succinct summary of notable predictive analytics models, their common uses in the petroleum industry, and pertinent references.

Table.2. Overview of Predictive Analytics Models in Oil & Gas

Model	Application	Strengths	Key References
Artificial Neural Networks (ANN)	Reservoir characterization, production forecasting	Captures nonlinear relationships	(Bhattacharya et al., 2019; Otchere et al., 2021)
Support Vector Machines (SVM)	Well-log analysis, classification of lithofacies	Good generalization, handles high-dim data	(Tewari & Dwivedi, 2019; Salem et al., 2022)
Random Forests	Classification tasks (e.g., deposit type), oil composition	Robust to overfitting, interpretable	(Rajković et al., 2023; Gupta et al., 2023)
Gradient Boosting Machines	Predicting permeability, porosity	High predictive performance	(Tariq et al., 2021; Schuetter et al., 2018)
Deep Neural Networks (DNN)	Price forecasting, reservoir simulation	Automated feature extraction	(Daneshvar et al., 2022; Jovanovic et al., 2022)
Adaptive Neuro-Fuzzy Inference	Quality control, property prediction	Explainable, adaptive to changing data	(AlRassas et al., 2021; Saghir et al., 2024)

3.3.1. Hybrid Models

Hybrid models are gaining popularity to capitalise on the capabilities of several algorithms. Hybrid methodologies may integrate artificial neural networks with fuzzy logic (i.e., neuro-fuzzy systems) or amalgamate several machine learning techniques to enhance resilience (Sabani et al., 2024; Lawal et al., 2024). Additional hybrids use metaheuristics that preprocess data, choose characteristics, or initialise model parameters (Al Jlibawi et al., 2021; Alzahawy & Issa, 2024). Rajabi et al. (2021) introduced a hybrid machine learning optimizer to forecast fracture density using petrophysical data, integrating Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) for feature selection and parameter tweaking.

3.3.2. Transfer Learning and Domain Adaptation

Although less prevalent in the petroleum industry compared to domains such as computer vision or natural language processing, transfer learning has started to garner interest for cross-reservoir predictions (Chen et al., 2024; Mardanshahi et al., 2025). The objective is to train a model on data from one reservoir and subsequently refine it with a restricted dataset from a fresh reservoir. This can markedly decrease the time and data demands for new model deployments, especially in contexts where acquiring labelled data is costly or labor-intensive (Siddiqui & Tabassum, 2024).

3.3.3. Big Data and Cloud-Based Analytics

As refineries increasingly adopt digital connectivity, the volume of data generated from sensors, logs, and production records is expanding dramatically (Ansari & Taqvi, 2023; Tariq et al., 2021). Cloud-based analytics and distributed computing solutions, such as Apache Spark, are being utilized for large-scale, real-time data processing (Tewari & Dwivedi, 2019). In this context, fuzzy control charts and machine learning models may be implemented as microservices, perpetually updated and accessible to operators and decision-makers via dashboards (Holdaway, 2012; Bhattacharya et al., 2019).
Figure 3 depicts a comprehensive system that encompasses data intake, pre-processing, model training (such as neuro-fuzzy methodologies), and metaheuristic optimization. The optimized model continually updates the fuzzy control charts,

establishing a feedback loop that refines both the model parameters and the control thresholds in real time.

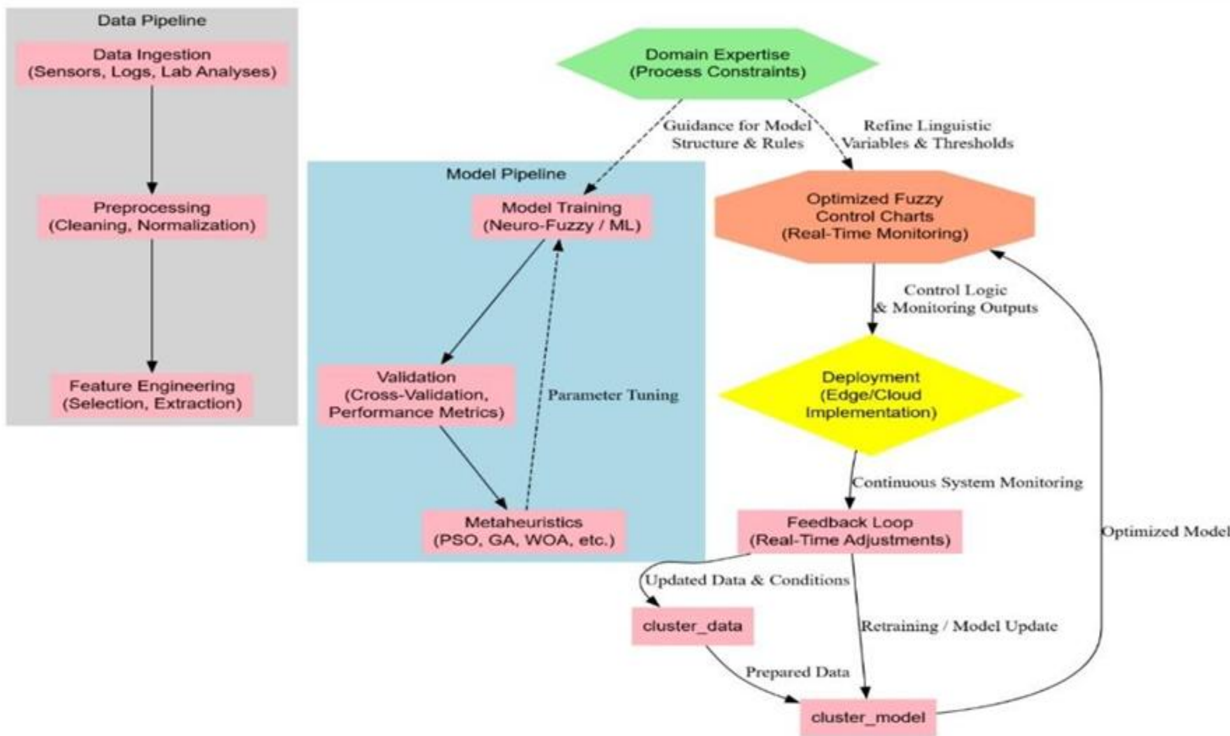

Fig.3 Integrated Optimization Approach with Fuzzy Control Charts

IV. CHALLENGES AND RESEARCH GAP

Despite considerable progress in the integration of fuzzy control charts, advanced optimization algorithms, and predictive analytics within the petroleum sector, several hurdles and deficiencies remain that obstruct extensive industrial adoption and optimal performance. Rectifying these deficiencies offers a chance to enhance the dependability and efficacy of petroleum quality assurance.

4.1.Data Quality and Heterogeneity

A primary difficulty is data quality (Nagargoje et al., 2023; N. Zhang et al., 2021). Sensor data may be compromised by noise, susceptible to absent values, or affected by varying sample rates. Moreover, data from various wells or refineries may change significantly due to geological variations or operating protocols (Tariq et al., 2021). Fuzzy control charts partially address this issue by accommodating imprecision; nonetheless, they do not completely eliminate systematic biases or address inadequate data (Morain et al., 2024). Future research may include rigorous data-cleaning protocols and sophisticated data imputation techniques, maybe including domain expertise (Mishra & Datta-Gupta, 2017).

4.2.Scalability and Real-Time Constraints

The majority of the literature emphasizes controlled tests or small-scale demonstrations (Al Jlibawi et al., 2021; Salem et al., 2022). Implementing scaling solutions for extensive refineries with varied product lines and multi-stage processes is intricate. Moreover, real-time analytics necessitate low-latency systems. Although current metaheuristics and machine learning algorithms provide remarkable accuracy, they may incur significant computational costs for real-time implementation (Bhattacharya et al., 2019). Future research should concentrate on high-performance computing systems, incremental or online learning techniques, and parallelizable optimization algorithms to satisfy real-time requirements (Siddiqui & Tabassum, 2024).

4.3.Integration with Domain Knowledge

Numerous sophisticated analytical models, such as neuro-fuzzy systems, are entirely data-driven (Pandey et al., 2021). The integration of chemical engineering concepts, thermodynamics, and reaction kinetics information can significantly enhance model correctness and interpretability (Karambeigi et al., 2023). Hybrid frameworks integrating mechanistic models—such as mass-balance or thermodynamic equations—with fuzzy control charts are yet inadequately investigated (Saghir et al., 2024).

4.4.Multi-Objective and Multi-Criteria Optimization

Quality management in petroleum refining is never a singular aim; it frequently necessitates trade-offs among economic feasibility, environmental limitations, and product quality (Wang et al., 2022). Although single-objective optimization, such as maximizing yield or minimizing sulphur content, is extensively researched, multi-objective frameworks that concurrently address yield, energy consumption, catalyst cost, and regulatory limitations are few (Karambeigi et al., 2023). In the future, employing multi-objective evolutionary algorithms alongside fuzzy logic may provide a more comprehensive perspective on optimization in petroleum refining (Chen et al., 2024).

4.5.Lifecycle Monitoring and Predictive Maintenance

An increasing volume of research highlights the significance of lifecycle monitoring, wherein quality assurance encompasses not just refinement but also downstream processes such as distribution and end product utilization (R. Azmi et al., 2024; Wang et al., 2022). Fuzzified control charts may effectively monitor the deterioration of stored fuels in pipes or tanks. Likewise, modern analytics can guide predictive maintenance methods for refinery equipment (Sabani et al., 2024; Siddiqui & Tabassum, 2024). Nonetheless, research that combines end-to-end lifetime monitoring with fuzzy-based optimization is few (Akbar et al., 2023).

4.6.Interpretability and Trust

In regulated sectors such as petroleum, explainability is not just advantageous but frequently a compliance need (Colaco et al., 2023). Although fuzzy control charts are fundamentally more interpretable than black-box models, the integration of metaheuristic tuning and deep architectures might conceal the reasoning behind certain operational setpoints (Jovanovic et al., 2022). Subsequent research may integrate eXplainable AI (XAI) methodologies to clarify the temporal evolution of membership functions or fuzzy rules (Benbouzid et al., 2021).

4.7.Research Gap Summary

The integration of fuzzy logic and advanced analytics in petroleum quality prediction, albeit promising, encounters challenges with data dependability, computing efficiency, multi-objective integration, and interpretability. Addressing these disparities necessitates collaborative endeavours among domain experts, data scientists, and control engineers to create really robust, scalable, and transparent systems (Mishra & Datta-Gupta, 2017; Salem et al., 2022).

V. CONCLUSION AND FUTURE WORK

This paper has analyzed the swiftly advancing convergence of fuzzy control charts, sophisticated optimization techniques, and predictive analytics for forecasting petroleum quality. The research highlights the increasing agreement that conventional statistical process control, although fundamental, is inadequate for addressing the intrinsic uncertainties, nonlinearities, and real-time requirements of contemporary refineries (Razali et al., 2024; Saghir et al., 2024). Fuzzy logic mitigates the constraints of strict thresholds by embracing the intrinsic vagueness in process data, while evolutionary and swarm-based algorithms function as effective mechanisms for optimizing these fuzzy systems in intricate, high-dimensional environments (Chen et al., 2024; Sun et al., 2022).

Neuro-fuzzy systems, such as ANFIS and its derivatives, integrate interpretability with adaptive learning, providing a flexible approach for the dynamic adjustment of control charts (AlRassas et al., 2021; Bhattacharya et al., 2019). The collaboration of fuzzy logic, machine learning, and metaheuristic optimization has demonstrated potential in small-scale or laboratory settings, with growing interest in expanding these solutions to industrial applications (Al Jlibawi et al., 2021). Nonetheless, challenges related to data quality, real-time adaptability, multi-objective restrictions, and interpretability persist (Pandey et al., 2021; Lawal et al., 2024).

Three principal research trajectories are anticipated moving forward. Integrating domain information more thoroughly into fuzzy systems and optimization algorithms can enhance both accuracy and system transparency (Mishra & Datta-Gupta, 2017; Karambeigi et al., 2023). Secondly, multi-objective optimization frameworks that consider product quality, environmental impact, and economic factors possess the capacity to provide more comprehensive decision support (Wang et al., 2022; Karatzinis & Boutalis, 2025). Third, the demand for real-time solutions will require scalable systems adept at managing extensive data streams, either through cloud or edge computing (Tariq et al., 2021; Jovanovic et al., 2022). Pursuing these lines of inquiry concurrently will enable the petroleum sector to benefit from more efficient, robust, and transparent control systems that use the finest aspects of fuzzy logic and sophisticated analytics.

In summary, the advancement of optimized fuzzy control charts—propelled by machine learning breakthroughs, effective metaheuristic optimization, and enhanced integration of domain-specific knowledge—indicates a significant possibility to improve petroleum quality control procedures. Rectifying the highlighted deficiencies and obstacles would facilitate the development of advanced control systems that are more precise, adaptable, safer, ecologically sustainable, and more suited to the intricate operational requirements of the contemporary petroleum sector.

REFERENCES

[1] Akbar, S., Vaimann, T., Asad, B., Kallaste, A., Sardar, M. U., & Kudelina, K. (2023). State-of-the-art techniques for fault diagnosis in electrical machines: advancements and future directions. Energies, 16(17), 6345.

[2] Alabdrabalnabi, A., Gautam, R., & Sarathy, S. M. (2022). Machine learning to predict biochar and bio-oil yields from co-pyrolysis of biomass and plastics. Fuel, 328, 125303.

[3] Al Jlibawi, A. H. H., Othman, M. L., Ishak, A., Noor, B. S. M., & Al Huseiny, M. (2021). Optimization of distribution control system in oil refinery by applying hybrid machine learning techniques. IEEE Access, 10, 3890-3903.

[4] AlRassas, A. M., Al-qaness, M. A., Ewees, A. A., Ren, S., Abd Elaziz, M., Damaševičius, R., & Krilavičius, T. (2021). Optimized ANFIS model using Aquila Optimizer for oil production forecasting. Processes, 9(7), 1194.

[5] Alzahawy, A., & Issa, H. (2024). Intelligent Petroleum Processing: A Short Review on Applying AI/ML to Petroleum Products Optimization.

[6] Ansari, T. S., & Taqvi, S. A. A. (2023). State-of-the-Art Review on the Applications of Nonlinear and Artificial Intelligence-Based Controllers in Petrochemical Processes. ChemBioEng Reviews, 10(6), 884–906.

[7] Azmi, R. P. A., Yusoff, M., & Mohd Sallehud-din, M. T. (2024). A Review of Predictive Analytics Models in the Oil and Gas Industries.Sensors, 24(12), 4013.

[8] Benbouzid, M., Berghout, T., Sarma, N., Djurović, S., Wu, Y., & Ma, X. (2021). Intelligent condition monitoring of wind power systems: State of the art review. Energies, 14(18), 5967.

[9] Bhattacharya, S., Ghahfarokhi, P. K., Carr, T. R., & Pantaleone, S. (2019). Application of predictive data analytics to model daily hydrocarbon production using petrophysical, geomechanical, fiber-optic, completions, and surface data: A case study from the Marcellus Shale, North America. Journal of Petroleum Science and Engineering, 176, 702–715.

[10] Chen, B., Cao, L., Chen, C., Chen, Y., & Yue, Y. (2024). A comprehensive survey on the chicken swarm optimization algorithm and its applications: State-of-the-art and research challenges. Artificial Intelligence Review, 57(7), 170.

[11] Choubey, S., & Karmakar, G. P. (2021). Artificial intelligence techniques and their application in oil and gas industry. Artificial Intelligence Review, 54(5), 3665–3683.

[12] Colaco, S. G., Varghese, S. G., Kurian, C. P., & Kumar, S. (2023). A state-of-the-art artificial intelligent technique in daylighting controller: models and performance. Science and Technology for Energy Transition, 78, 37.

[13] Daneshvar, A., Ebrahimi, M., Salahi, F., Rahmaty, M., & Homayounfar, M. (2022). Brent

crude oil price forecast utilizing deep neural network architectures. Computational Intelligence and Neuroscience, 2022(1), 6140796.

[14] Gupta, N. S., Mohta, Y., Heda, K., Armaan, R., Valarmathi, B., & Arulkumaran, G. (2023). Prediction of air quality index using machine learning techniques: a comparative analysis. Journal of Environmental and Public Health, 2023(1), 4916267.

[15] Holdaway, K. R. (2012, April). Predictive Analytics: Development and Deployment of Upstream Data Driven Models. In SPE Latin America and Caribbean Petroleum Engineering Conference (pp. SPE-153454). SPE.

[16] Jovanovic, L., Jovanovic, D., Bacanin, N., Jovancai Stakic, A., Antonijevic, M., Magd, H., ... & Zivkovic, M. (2022). Multi-step crude oil price prediction based on LSTM approach tuned by salp swarm algorithm with disputation operator. Sustainability, 14(21), 14616.

[17] Karatzinis, G. D., & Boutalis, Y. S. (2025). A Review Study of Fuzzy Cognitive Maps in Engineering: Applications, Insights, and Future Directions. Eng, 6(2), 37.

[18] Karambeigi, M. S., Hasan-Zadeh, A., Karambeigi, M. S., Rastegar, S. A. F., Nasiri, M., & Kazemzadeh, Y. (2023). Multi-objective optimization of petroleum engineering problems using a hybrid workflow: Combination of particle swarm optimization, fuzzy logic, imperialist competitive algorithm and response surface methodology. Geoenergy Science and Engineering, 224, 211579.

[19] Lawal, A., Yang, Y., He, H., & Baisa, N. L. (2024). Machine Learning in Oil and Gas Exploration—A Review. IEEE Access.

[20] Mardanshahi, A., Sreekumar, A., Yang, X., Barman, S. K., & Chronopoulos, D. (2025). Sensing Techniques for Structural Health Monitoring: A State-of-the-Art Review on Performance Criteria and New-Generation Technologies. Sensors, 25(5), 1424.

[21] Mendes, E., & Duarte, N. (2021). Mid-infrared spectroscopy as a valuable tool to tackle food analysis: A literature review on coffee, dairies, honey, olive oil and wine. Foods, 10(2), 477.

[22] Mgbechidinma, C. L., Zheng, G., Baguya, E. B., Zhou, H., Okon, S. U., & Zhang, C. (2023). Fatty acid composition and nutritional analysis of waste crude fish oil obtained by optimized milder extraction methods. Environmental Engineering Research, 28(2).

[23] Mishra, S., & Datta-Gupta, A. (2017). Applied statistical modeling and data analytics: A practical guide for the petroleum geosciences.Elsevier.

[24] Morain, A., Ilangovan, N., Delhom, C., & Anandhi, A. (2024). Artificial Intelligence for Water Consumption Assessment: State of the Art Review. Water Resources Management, 38(9), 3113–3134.

[25] Motaei, E., & Ganat, T. (2023). Smart proxy models art and future directions in the oil and gas industry: A review. Geoenergy Science and Engineering, 227, 211918.

[26] Nagargoje, A., Kankar, P. K., Jain, P. K., & Tandon, P. (2023). Application of artificial intelligence techniques in incremental forming: a state-of-the-art review. Journal of Intelligent Manufacturing, 34(3), 985–1002.

[27] Otchere, D. A., Ganat, T. O. A., Gholami, R., & Ridha, S. (2021). Application of supervised machine learning paradigms in the prediction of petroleum reservoir properties: Comparative analysis of ANN and SVM models. Journal of Petroleum Science and Engineering, 200, 108182.

[28] Pandey, R. K., Dahiya, A. K., & Mandal, A. (2021). Identifying applications of machine learning and data analytics-based approaches for optimization of upstream petroleum operations. Energy Technology, 9(1), 2000749.

[29] Quadri, T. W., Akpan, E. D., Elugoke, S. E., Olasunkanmi, L. O., Sheetal, S., Singh, A. K., ... & Ebenso, E. E. (2025). State-of-the-art progress on artificial intelligence and machine learning in accessing molecular coordination and adsorption of corrosion inhibitors. Applied Physics Reviews, 12(1).

[30] Rajabi, M., Beheshtian, S., Davoodi, S., Ghorbani, H., Mohamadian, N., Radwan, A. E., & Alvar, M. A. (2021). Novel hybrid machine learning optimizer algorithms to prediction of fracture density by petrophysical data. Journal of Petroleum Exploration and Production Technology, 11(12), 4375–4397.

[31] Rajković, D., Jeromela, A. M., Pezo, L., Lončar,

B., Grahovac, N., & Špika, A. K. (2023). Artificial neural network and random forest regression models for modelling fatty acid and tocopherol content in oil of winter rapeseed. Journal of Food Composition and Analysis, 115, 105020.

[32] Razali, N. H. M., Abdullah, L., Ab Ghani, A. T., Afthanorhan, A., & Zabihinpour, M. (2024). A Type-2 Fuzzy u-Control Chart Considering Probability-Based Average Run Length. Contemporary Mathematics, 959–977.

[33] Sabani, E., Loualid, E. M., Fakir, K., El Hadraoui, H., Ennawaoui, C., & Azim, A. (2024). Statistical Control Charts for Proactive Bearings Fault Diagnosis in Turbines: Advancing Predictive Maintenance in Renewable Energy Systems. Journal of Vibration Engineering & Technologies, 1–15.

[34] Saghir, H., Ahmad, I., Kano, M., Caliskan, H., & Hong, H. (2024). Prediction and optimization of gasoline quality in petroleum refining: The use of machine learning model as a surrogate in optimization framework. CAAI Transactions on Intelligence Technology.

[35] Salem, A. M., Yakoot, M. S., & Mahmoud, O. (2022). Addressing diverse petroleum industry problems using machine learning techniques: literary methodology spotlight on predicting well integrity failures. ACS omega, 7(3), 2504–2519.

[36] Schuetter, J., Mishra, S., Zhong, M., & LaFollette, R. (2018). A data-analytics tutorial: Building predictive models for oil production in an unconventional shale reservoir. SPE Journal, 23(04), 1075–1089.

[37] Shaamala, A., Yigitcanlar, T., Nili, A., & Nyandega, D. (2024). State-of-the-art machine learning models for geospatial analysis: a systematic review of urban and environmental studies. Available at SSRN 4728438.

[38] Siddiqui, M. M. U. Z., & Tabassum, A. (2024). Condition-based monitoring techniques and algorithms in 3d printing and additive manufacturing: a state-of-the-art review. Progress in Additive Manufacturing, 1–48.

[39] Song, Y., Wang, X., Li, H., He, Y., Zhang, Z., & Huang, J. (2022). Mixture optimization of cementitious materials using machine learning and metaheuristic algorithms: State of the art and future prospects. Materials, 15(21), 7830.

[40] Sravan, K., Rao, L. G., Ramineni, K., Rachapalli, A., & Mohmmad, S. (2024). Analyze the Quality of Wine Based on Machine Learning Approach Check for updates. Data Science and Applications: Proceedings of ICDSA 2023, Volume 3, 820, 351.

[41] Stone, P. (2007, April). Introducing predictive analytics: Opportunities. In SPE Digital Energy Conference and Exhibition (pp. SPE-106865). SPE.

[42] Sun, Y., Zhang, J., Yu, Z., Liu, Z., & Yin, P. (2022). WOA (Whale Optimization Algorithm) optimizes elman neural network model to predict porosity value in well logging curve. Energies, 15(12), 4456.

[43] Tashtoush, B., Alyahya, W. E., Al Ghadi, M., Al-Omari, J., & Morosuk, T. (2023). Renewable energy integration in water desalination: State-of-the-art review and comparative analysis. Applied Energy, 352, 121950.

[44] Tariq, Z., Aljawad, M. S., Hasan, A., Murtaza, M., Mohammed, E., El-Husseiny, A., ... & Abdulraheem, A. (2021). A systematic review of data science and machine learning applications to the oil and gas industry. Journal of Petroleum Exploration and Production Technology, 1–36.

[45] Tewari, S., & Dwivedi, U. D. (2019). Ensemble-based big data analytics of lithofacies for automatic development of petroleum reservoirs. Computers & Industrial Engineering, 128, 937–947.

[46] Ullah, Z., Naqvi, S. R., Farooq, W., Yang, H., Wang, S., & Vo, D. V. N. (2021). A comparative study of machine learning methods for bio-oil yield prediction–a genetic algorithm-based features selection. Bioresource Technology, 335, 125292.

[47] Wang, C. N., Nhieu, N. L., Tran, K. P., & Wang, Y. H. (2022). Sustainable integrated fuzzy optimization for multimodal petroleum supply chain design with pipeline system: The case study of Vietnam. Axioms, 11(2), 60.

[48] Xue, Z., Niu, S., Chau, A. M. H., Luo, Y., Lin, H., & Li, X. (2023). Recent advances in multi-phase electric drives model predictive control in renewable energy application: A state-of-the-art review. World Electric Vehicle Journal, 14(2), 44.

[49] Yousef, A. M., Kavousi, G. P., Alnuaimi, M., &

Alatrach, Y. (2020). Predictive data analytics application for enhanced oil recovery in a mature field in the Middle East. Petroleum Exploration and Development, 47(2), 393–399.

[50] Zhang, N., Li, Y., Wen, S., Sun, Y., Chen, J., Gao, Y., & Yu, X. (2021). Analytical methods for determining the peroxide value of edible oils: A mini-review. Food Chemistry, 358, 129834.