A Review of Optimized Fuzzy Control Charts for Petroleum Quality Improvement: Emerging Trends and Future Directions

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doi.org/10.64643/IJIRTV12I12-202446-459

***Abstract* - The petroleum industry demands high-grade regulatory conformity processes for safety and homogeneity of the product. Traditional statistical process control (SPC) processes lack the ability for handling fuzzy and inaccurate data. This review explains the development of optimized fuzzy control charts for petroleum quality enhancement with their ability to handle process variation in uncertain settings. This article reviews recent literature on the optimization analysis of various methods, such as artificial intelligence (AI)-based tuning, adaptive thresholding, and hybrid approaches based on machine learning models. The review also addresses fuzzy logic-based integration with conventional SPC methods, such as their applications in refining, transportation, and storage. Detection sensitivity, false alarm rate, and adaptability to changing process conditions are the main performance metrics analyzed. Results indicate that optimized fuzzy control charts outperform traditional control charts with increased flexibility and robustness in quality monitoring. AI-based fuzzy models demonstrate improved accuracy in detecting deviations, reducing false alarms, and optimizing control limits based on real-time process variations. The integration of deep learning technology with evolutionary algorithms also enhances predictive capabilities in optimized fuzzy control charts and places them in an even stronger position in extremely complex petroleum processing scenarios. Applications in real life also prove to be effective in refining operations, fuel blending, and detection of contaminations. Improved fuzzy control charts are an important step to enhance petroleum quality control, as they overcome the shortcomings of conventional SPC techniques in uncertain settings. Integration of AI, fuzzy logic, and big data analytics will likely continue to revolutionize quality control measures, making them more efficient and sustainable in petroleum production.**

***Keywords:* Fuzzy control charts, Fuzzy Models, SPC, Petroleum Production.**

I. INTRODUCTION

1.1 Background

Petroleum is a key component in the world economy by providing fuel and raw materials for industries like transport, manufacturing, and power generation. The importance of petroleum products quality assurance is used for operational performance and the prevention of environmental and economic hazards. Many of the traditional statistical process control (SPC) tools, including the Shewhart and Cumulative Sum (CUSUM) control charts, used for the quality monitoring for petroleum refinery processes. To counter this, researchers introduced fuzzy control charts, where fuzzy set theory is combined alongside traditional SPC tools. Fuzzy control charts allow flexible decision-making by the use of linguistic variables like "slightly out-of- control" and "moderately stable" for the expression of the processes' state. In the petroleum industry, the need for high-product quality is combined with the need for lowered costs and lowered impacts upon the environment [1]. Statistical process control (SPC) is very important for the achievement of process capability and improvement through the prevention of variability. It established the α-cut fuzzy control charts to be used in attribute control charts. The development of fuzzy theory where type-1 fuzzy sets were extended to type-2 fuzzy sets, the knowledge of control charts was also developed. In an attempt to include type-2 fuzzy sets in control charts, type-2 fuzzy mean (X) and range (R) control charts [2].

1.2 Definition of the Problem

Quality control of the petroleum industry is a challenge due to the complexity of the process of refining and natural variations of crude. Traditional SPC techniques, such as Shewhart and Exponentially Weighted Moving Average (EWMA) control charts, rely on precise numeric measurements and normal distribution of process data [3]. Fuzzy control charts offer a solution with the employment of fuzzy logic for uncertain and ambiguous data. With contrast from traditional control charts, where there are predetermined boundaries of control, fuzzy control charts apply membership functions for varying levels of process variations. Fuzzy control charts, with their advantages, must be optimized for their performance. Challenges such as optimal choice of membership functions, optimal setting of fuzzy rules, and real-time data analytics need to be addressed for their extensive employment in surveillance of petroleum quality.

1.3 Purpose of this study
The primary objective of this study is the review and study of optimized use of fuzzy control chart for quality improvement in the petroleum industry. The study aims to explore the utilization of fuzzy control charts, with the use of fuzzy logic for handling uncertainty, for quality monitoring in the process of producing petroleum [4]. Through the review of the most up-to-date advancements in research on methods of optimization, such as adaptive fuzzy models, genetic algorithms, and hybrid machine learning techniques, this study aims to find improvements in accuracy of detection and process stability [5]. The study also examines real-world applications of optimized use of fuzzy control chart in petroleum refining, fuel blending, and pipeline surveillance, comparing their advantages with conventional SPC methods.

1.4 Review of Optimized Fuzzy Control Charts for Improving the Quality of Petroleum
Optimized fuzzy control charts were a useful tool for quality control for the petroleum industry, primarily for dealing with process uncertainties and imprecise data. The traditional Statistical Process Control (SPC) techniques, such as Shewhart and Exponentially Weighted Moving Average (EWMA) control charts, rely on data normal distribution and precise numeric measurements. With the employment of fuzzy logic with SPC techniques, fuzzy control charts can more effectively detect small variations, reduce false alarm rates, and allow for more effective decision-making for quality surveillance of petroleum.

These studies highlight the enhancement of fuzzy membership functions, optimal setting of the control limits, and integrating more complex algorithms for enhanced performance of the fuzzy control chart. A review of significant contributions in this context follows:

- Quality Improvement of Petroleum Products Using Fuzzy Control Charts: In the fuzzy control charts for quality monitoring of petroleum products in the Al-Dura Refinery. The α-level fuzzy midrange technique for addressing uncertain data on quality of petroleum. The research concluded that employment of fuzzy control charts provides greater flexibility and accuracy of quality measurement compared with traditional SPC.
- Applying Fuzzy Control Charts for Detection of Optimum Limits in the Petroleum Sector: It also proposed a more improved methodology for designing fuzzy control charts with greater identification of optimal boundaries of control in uncertain environments. Using SPC and fuzzy logic, the authors designed a more flexible model for process variations, reducing the likelihood of producing faulty petroleum products.
- Optimization of Fuzzy Control Energy Management Strategy for Fuel Cell Vehicle: While not focusing on petroleum quality control directly, conducted research on the advancement of fuzzy control techniques for energy management of fuel cell vehicles. The study employed methods such as genetic algorithm (GA) for tuning of fuzzy membership functions, and this improved fuel economy [6].

Key Insights from the Review:
From these research papers, the following major conclusions can be drawn for optimized fuzzy control charts for enhanced quality of petroleum:

- Enhanced Handling of Uncertainty: Fuzzy control charts are more tolerant of process variability compared with traditional SPC techniques.
- Optimization Improves Performance: Some of the techniques of optimization, such as genetic algorithm (GA), particle swarm optimization (PSO), and Cuckoo Search (CS), enhance the performance of fuzzy control charts [7].

Contributions of these studies are as follows:

- This study reviews the up-to-date research on optimized fuzzy control charts and provides a systematic review of their application in quality surveillance of petroleum.

- It proposes future research directions, including combining artificial intelligence (AI) and Internet of Things (IoT) technologies for enhanced real-time monitoring of refineries.
- This study examines various approaches of optimization, such as genetic algorithm (GA), particle swarm optimization (PSO), and Cuckoo Search (CS) for the improvement of performance of fuzzy control charts.

II. LITERATURE REVIEW

2.1 Fuzzy Quality Control Charts

The research implements crude oil reduced prediction at refining process field stage one by developing soft sensor models using adaptive neuro-fuzzy inference system (ANFIS) with rough set theory (RST) to optimize oil refinery performance. Analysts used the RST to truncate the fuzzy rules that exist in ANFIS but employed its features across the decision table. The prediction system determines light naphtha product quality based on Reid Vapor Pressure (RVP) and American Petroleum Institute gravity (API gravity). By implementing an ANFIS based cascade control system the rise time performance increased by 26.65% while the settling time achieved 84.63% more efficiency than traditional PID cascade control [8].

Petroleum supply chain efficiency acts as a primary economic determinant because it directly affects the performance of economic operations. The proposed research integrates two solution approaches through exact optimization methods with heuristic algorithms. The proposed model uses Fuzzy Min-Max Goal Programming Model (FMMGPM) to identify multiple objective solutions. This model analyzes supply chain uncertainty through simultaneous evaluation of factors including demand and resource as well as cost and price. A sensitivity analysis with constructed scenarios based on range and probability levels of uncertainty was performed to examine design decision effects by this research [9].

The control methods of quality control charts work within single production characteristics but they require significant observational data to identify stable control boundaries. A fundamental drawback of traditional control charts exists because they lack functionality in dealing with indistinct data environments. The fuzzy control charts handle data variations by design since they deal with existing data uncertainties [10].

2.2 Optimized Fuzzy Logic Control

The research develops Particle Swarm Optimization (PSO) based Fuzzy Logic Controller (FLC) for battery energy storage system (ESS) scheduling and charging-discharging in microgrid (MG) applications to reduce grid power consumption and operational costs. The control of battery charging and discharging receives optimization through PSO-based variation of FLC membership functions under available power and load demand and battery temperature and state of charge (SOC) conditions. Results show that the developed PSO-based fuzzy control achieves efficient battery management while decreasing power consumption from the grid by 42.26% and reducing energy costs by 45.11% [11].

The oil and gas production operations suffer from inadequate management of parallel business processes which include field exploration along with their arrangement and development as well as the production and sale of petroleum products. The paper introduced a decision tree model illustrating the optimal investment management process through which an oil and gas enterprise finds hydrocarbons in present-day economic frameworks followed by further developments of hybrid technology principles and knowledge-oriented foundations alongside uncertainty management strategies during investment decision support for oil and gas organizations [12].

Modern industry relies heavily on crude oil which functions as an essential worldwide infrastructure of energy production. The research develops established Spherical Fuzzy Set theory by introducing Disc Spherical Fuzzy Sets (D-SFSs) for decision support in critical crude oil preparation processes. Multiple Attribute Group Decision Making serves as a framework that combines aggregation procedures into a single solution. This study achieves a major advancement in decision-making capability through a complete framework specific to complex critical domains that include crude oil pretreatment [13].

The research focuses on analyzing how effective optimized fuzzy logic control becomes when used in real-time swing-up control and rigid coupling stabilization of twin-arm inverted pendulum systems. System controllers implement black-box methods for design purposes without requiring precise mathematical system models. The experimental results confirms that the controlled system provides enhanced short-term along with prolonged response capabilities compared to existing state-of-the-art controllers [14].

This article proposes a new control scheme for Dynamic Voltage Restorer (DVR) in utility grid distribution systems will be presented in this article. The proposed algorithm delivers a complex cost-efficient answer to address power quality challenges. The outcomes demonstrate that basis DVR systems using PI tuned fuzzy logic controllers achieve superior performance regarding voltage mitigation for harmonic suppression than traditional DVR systems. The research focuses on the examination of DVR systems through the implementation of PI-adjusted fuzzy control to create an advanced distribution system control solution [15].

Energy storage technology operates as a solution to boost the fuel efficiency of fuel cell system (FCS). Researchers developed a novel approach to maximize the performance of fuel cell vehicle EMS strategies for lowering fuel use in this research. The researchers used multi-island genetic algorithm to optimize the MFs. Two driving cycles powered simulations demonstrated the optimization success of the fuzzy control EMS with an optimal method for controller performance. By implementing an optimized EMS system, it becomes possible to decrease hydrogen need and boost fuel economy while also extending the lifespan of the fuel cell [16].

The present power system comprises renewable integration and accelerating non-linear industrial and commercial loads which leads to multiple power quality issues. Harmonic injection occurs along with reactive power imbalance as a result of widespread divergence between power system components. The power quality solution known as Distribution Static Compensator (DSTATCOM) provides simultaneous benefits in harmonic mitigation and load balancing together with reactive power balancing and neutral current compensation. The proposed methodology achieves better harmonic control performance than both Type 1 fuzzy logic controller and Conventional PI controller [17].

III. OPTIMIZED FUZZY CONTROL CHARTS FOR PETROLEUM QUALITY IMPROVEMENT

This section provides the details of Optimized Fuzzy Control Charts for Petroleum Quality Improvement.

3.1. Optimized fuzzy control chart design

The quality of petroleum products plays an essential role in enhancing operational processes as well as maintaining safety measures and customer satisfaction levels. Traditional Statistical Process Control (SPC) control charts function for quality monitoring but they are unable to control the uncertainties within process variability and data measurement accuracy. The section provides an optimized design of fuzzy control charts to enhance petroleum quality through an explanation of methods while illustrating components and evaluation of uncertain data handling [18].

3.1.1 Fundamentals of Fuzzy Control Charts

The integration of fuzzy set theory with SPC in fuzzy control charts allows process data monitoring through handling uncertain measurements and imprecision. The primary function of fuzzy control charts diverges from traditional control charts by employing fuzzy numbers to create control limits because these methods prove more effective in uncertain process environments. The essential aspects of fuzzy control charts consist of:

- Fuzzy Sets and Membership Functions: Process data takes the form of fuzzy numbers consisting of triangular or trapezoidal shapes to represent membership functions that establish measurement levels within the set structures.
- α-Cut Approach: Control limits in the α-cut approach receive their values by finding the fuzzy midrange of process variations through this method.
- Fuzzy Arithmetic Operations: The application of fuzzy arithmetic operations enables calculation of process mean and standard deviation along with control limit determination for fuzzy numbers.
- Flexibility in Decision-Making: The integration of confidence degrees within fuzzy control charts enhances quality

monitoring through decreased false alarm detections for better decision-making.

3.1.2. Methodology for Optimized Fuzzy Control Chart Design

Optimized fuzzy control charts for petroleum quality improvement proceed through the following method in Fig 1.

Figure.1. Fuzzy Control Charts

Step 1: Data Collection and Problem Definition: The initial step requires gathering data for defining the problem. The selected data collection covers petroleum processes that measure quality aspects.

Step 2: Selection of Control Chart Type: A selection of the suitable fuzzy control chart happens according to the data type. Common types include:

- Fuzzy X̄ - R Chart: Used for monitoring process mean and range.
- Fuzzy X̄ - S Chart: Process standard deviation for suitable measure for variability depending on which method among fuzzy X̄ - S Charts is utilized.
- Fuzzy Attribute Control Charts: The fuzzy attribute control charts for monitoring categorial data such as defect classification systems.

Step 3: Calculation of Fuzzy Control Limits: The third step involves computing fuzzy control limits through fuzzy arithmetic methods together with the α-cut methodology. Prediction of fuzzy control limits occurs through the usage of fuzzy arithmetic and the α-cut method. General formulas for X̄ - R fuzzy control charts appear as follows:

i. Fuzzy X̄ Chart Control Limits:

- Center Line $(\tilde{CL}) = (\bar{\bar{X}}_a, \bar{\bar{X}}_b, \bar{\bar{X}}_c)$
- Lower Control Limit $\tilde{(LCL)} = (\bar{\bar{X}}_a - A_2\bar{R}_c, \bar{\bar{X}}_b - A_2\bar{R}_a, \bar{\bar{X}}_c - A_2\bar{R}_a)$
- Upper Control Limit $(\hat{UCL}) = (\bar{\bar{X}}_a + A_2\bar{R}_a, \bar{\bar{X}}_b + A_2\bar{R}_b, \bar{\bar{X}}_c + A_2\bar{R}_c)$

ii. Fuzzy R Chart Control Limits:

- $\tilde{CL}) = (\bar{R}_{\bar{\bar{a}}}, \bar{R}_{\bar{\bar{b}}}, \bar{R}_{\bar{c}},)$
- $\tilde{(LCL)} = (D_3\, \bar{R}_{\bar{\bar{a}}}, D_3\, \bar{R}_{\bar{\bar{b}}}, D_3\, \bar{R}_{\bar{c}})$
- $(\hat{UCL}) = (D_4\, \bar{R}_{\bar{\bar{a}}}, D_4\, \bar{R}_{\bar{\bar{b}}}, D_4\, \bar{R}_{\bar{c}})$

The fuzzy mean X̄i together with fuzzy range R̄ defines the control limits.

Step 4: Data Transformation and Fuzzification: The conversion of process data into fuzzy numbers takes place through fuzzification procedures. The triangular and the trapezoidal fuzzy numbers comprise the fundamental fuzzy number groups.

- Triangular Fuzzy Numbers (TFN): Triangular Fuzzy Number takes the form (a, b, d) due to the middle value being the membership function value 'b'.
- Trapezoidal Fuzzy Numbers (TrFN): Uncertainty is described by TrFN and is associated with four parameters (a, b, c, d).

Step 5: Decision Rules and Process Monitoring: The decision rules together with process monitoring take place in Step 5. The evaluation of process data points happens through fuzzy control limits to check process control status. The decision rules: If LCLα$\bar{\bar{X}}$ ≤ Smr−X.$\bar{j}$≤ UCLα$\bar{\bar{X}}$, the process is in control.

- If LCLαmr− R̄ ≤ Smr−R j ≤ UCLαmr− R̄, the process is in control.
- Additional corrective actions should be initiated if the process moves out of its control limits

3.1.3. Case Study: Application in Petroleum Quality Control

A fuzzy control chart evaluation was carried out in a petroleum refinery context to monitor octane number specifications. The X̄ chart indicated eleven out-of-control samples among 35 intervals while the R chart detected one such sample. When the refinery used fuzzy control charts it found that the X̄ chart had four out-of-control samples yet all examined values fell within control limits in the R̄ chart. This demonstrates:

- Reduction in False Alarms: The traditional control chart system produces numerous unnecessary out-of-control alerts due to its proximity to control limits.
- Greater Process Stability: The refined evaluation made by fuzzy control charts improves overall assessment quality.
- Improved Quality Monitoring: Process stability increases through fuzzy control charts because these systems maintain adaptability toward minor fluctuations which prevents unnecessary interruptions.

3.1.4. Advantages of Optimized Fuzzy Control Charts

- Enhanced Accuracy: Data imprecision becomes an integrated factor through fuzzy logic to prevent process deviation misclassification.
- Better Adaptability: The flexibility of control limits enables better process adaptation which thus prevents false alarms during operations.
- Efficient Decision-Making: Improved decision-making efficiency occurs because the system provides dependable monitoring which enables prompt corrective actions.
- Reduced Process Downtime: Minimization of the occurrence of false alarms decreases the production downtimes thus resulting in reduced operating costs.
- Robustness in Real-World Applications: Robustness is demonstrated by the technology when deployed in real-life situations like petroleum refinery processes.

3.2 Petroleum Quality Improvement

The oil and gas industry's essential requirement for petroleum quality improvement enables petroleum products to fulfill their necessary standards for operational efficiency and safety alongside environmental compliance. Quality enhancement of petroleum products requires advanced refining methods combined with control systems and technological advancements. The application of fuzzy control charts presents itself as a promising methodology because they help organizations achieve better monitoring and quality assurance capabilities [19].

3.2.1 Importance of Petroleum Quality Improvement

Petroleum product quality directly determines their operational performance when used by both industrial operations and consumers. The use of high-quality petroleum products leads to cleaner emissions and better engine performances and increases fuel efficiency levels. Petroleum quality enhancement leads to lower environmental footprint during combustion operations while simultaneously decreasing costs required to maintain machinery and vehicles.

3.2.2 Methods of Petroleum Quality Improvement

Several techniques help improve petroleum quality through refining operations together with additive applications and strict quality management systems.

i. Refining Processes

Refining plays a fundamental role in improving petroleum quality. The key refining methods include:

- Fractional Distillation: Fractional Distillation operates through temperature-based boiling point separation to produce refined petroleum fractions that satisfy quality needs.
- Hydrocracking and Catalytic Cracking: Catalytic Cracking together with Hydrocracking operates on heavy hydrocarbon chains to split them into cleaner valuable fuel products which range from gasoline to diesel.
- Hydrotreating: The hydrotreating process removes sulfur and nitrogen impurities from gasoline while also improving the fuel characteristics to reduce fuel emissions
- Desulfurization: Petroleum product desulfurization activities help reduce harmful emissions while fulfilling environmental regulations through contaminant removal methods.

ii. Use of Additives

The petroleum industry includes additives to petroleum products which enhances their operational quality alongside improving their structural stability. Some common additives include:

- Anti-knock agents: Increased fuel

combustion efficiency.

- Corrosion inhibitors: Inhibit the corrosion of tanks and pipes.
- Detergents: Prevent carbon engines for development.
- Lubricity enhancers: Minimize the wear and tear in the fuel system.

iii. Quality Control Measures

Quality control processes ensure the petroleum products comply with specifications that regulate and provide levels of performance. Fuzzy control charts represent one of the modern techniques used in quality control practices.

3.2.3 Fuzzy Control Charts in Quality Monitoring

Standard statistical process control (SPC) charts serve as traditional methods to monitor petroleum quality in quality control processes. Petroleum data contains uncertainties because measurement errors combine with environmental condition variations. Fuzzy control charts enable better control by using fuzzy logic systems in quality monitoring processes.

3.2.4 Advantages of Fuzzy Control Charts:

- Handling Uncertainty: Fuzzy logic effectively deals with uncertain and variable data points that frequently appear during petroleum refining operations.
- Better Decision-Making: Better quality assessment decisions result from using fuzzy control charts that enable refineries to identify quality deviations with higher precision leading to instant corrective actions.
- Improved Performance: Fuzzy logic applied control charts ensure enhanced performance through the ability to accurately track the specification of the product, thus reducing defects and enhancing efficiency during operation.

3.2.5 Case Studies in Petroleum Quality Improvement

Petroleum refineries achieved superior quality monitoring through fuzzy control charts. An experiment by the Al-Dura refinery in Iraq validated fuzzy control charts provided superior control over the level of sulfur in the kerosene by preventing the process from being out-of- control much superior to the traditional SPC processes. Application of fuzzy control charts for the measurement of the octane level during the process of manufacturing benzene set the level of quality measurement very accurately for the complete conformity required by stringent industry specifications. Petroleum quality has to improve continuously because this improvement allows for maximum operation by minimizing emissions and regulatory specifications conformity. Merging innovative processes for petroleum refinery processes and additive incorporation processes and fuzzy control chart processes allows the manufacturer to realize maximum levels of petroleum quality.

3.3 Fuzzy control charts with machine learning algorithm

The petroleum industry needs strict quality control for maintaining product homogeneity, conformity with regulations, and safety. The conventional statistical process control (SPC) techniques find it challenging to manage uncertain, ambiguous, and vague data prevalent in the process of producing petroleum. To overcome this, fuzzy control charts present a smart and adaptive solution with the use of fuzzy set theory and machine learning techniques in Fig.2 The optimized chart can manage the natural variability of the quality parameters of petroleum, enabling more accurate monitoring and decision-making [20].

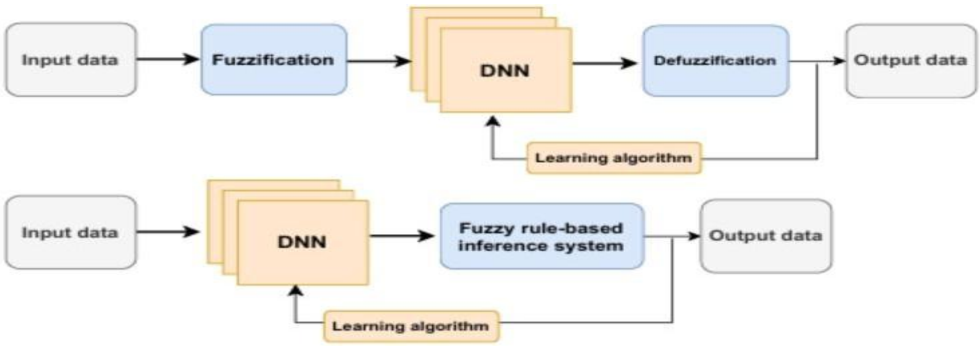

Figure.2. Fuzzy control with machine learning algorithm

3.3.1 Optimization Techniques for Fuzzy Control Charts

Optimizing fuzzy controllers consists of choosing optimal fuzzy membership functions, rule based, and learning mechanisms for enhanced accuracy. The techniques generally used for this purpose are:

- Genetic Algorithms (GA): Optimizing Fuzzy Rule Bases and Parameters of Membership Functions
- Particle Swarm Optimisation (PSO): Optimises the fuzzy parameters for maximum flexibility under variable environments.
- Adaptive Neuro-Fuzzy Inference Systems (ANFIS): Combines the use of fuzzy logic and neural networks for increased responsiveness of the control chart.
- Multi-Objective Optimization: Balances accuracy and computational performance when tuning the fuzzy model.

3.3.2 Fuzzy Control Charts with Machine Learning

The integration of machine learning with fuzzy control charts boosts their predictive and adaptive performance in complex petroleum producing environments. Some of the primary machine learning techniques used with fuzzy control charts are:

- Support Vector Machines (SVM) for Anomaly Detection: SVMs help discover abnormalities in data on petroleum quality by identifying non-linear trends and dependencies. Coupled with fuzzy control charts, SVMs boost the ability of differentiating between normal and out-of-control process variations. The SVM model classifies quality deviations with levels of confidence, and these can be measured with fuzzy membership functions, with smooth transition between quality levels of unacceptability and acceptability.
- Deep Learning for Pattern Detection: Deep learning networks, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), analyze huge datasets for minute quality variations of petroleum. With the use of fuzzy logic, these networks generate interpretable knowledge of quality variations. CNNs, for example, analyze image data from petroleum testing systems, and RNNs analyze sequence data from quality parameters' trends and abrupt variations from sensors.
- Reinforcement Learning for Adaptive Control: Reinforcement learning (RL) can be employed for dynamically modifying the control boundaries of fuzzy control charts with real-time feedback. RL can be of significant use for adaptive process control for dynamically changing process conditions of petroleum refineries. RL can learn optimal policies for control from experience, with trial and error, and, with experience, can also learn optimal fuzzy rule sets for maximum performance and minimum defects.
- Hybrid Fuzzy-ML Methods: Hybrid models combined machine learning and fuzzy logic for increased control precision. Examples are:
- Fuzzy Decision Trees: Improve the classification effectiveness for the identification of petroleum contamination by applying hierarchical decision rules and fuzzy thresholds.\
- Fuzzy K-Means Clustering: Diversifies the quality data into notable groups for easier trend observance, reducing the impact of fuzzy measurements and outlier data.
- Fuzzy Bayesian networks: Enhance process control's probabilistic reasoning, where operators can obtain knowledge about the likelihood of defects from historical data and the process state.

3.3.3 Case Study: Fuzzy Control of Crude Oil Processing Using Machine Learning

A real-world example of the use of fuzzy control chart with machine learning demonstrates their effectiveness. A hybrid ML-fuzzy solution for measuring sulfur content in crude oil in a refinery ensures process improvement. The raw data points are preprocessed with fuzzy logic, assigning values of membership for low, moderate, and high sulfur content levels, generating a more adaptive assessment model. The historical data and real-time data are assessed by machine models such as SVM and deep-learning models for trend and deviation detection and forecasting before the levels of significant quality.

The bar chart in Fig 3 and comparing the performance in improvement of petroleum quality under different optimization methods, with the accuracy percentage varying between about 10% and 35% using different methods. The performance metrics, and show that some fuzzy control chart optimizations can yield a up to 35% improvement, whereas others don't even breach 20%. The density graphs in Fig 4 that also shows the quality improvement rates, however what is interesting is that one of the optimization methods offers a mode around 30%, whilst the other around 20%, indicating there is more variability. Daily forecast optimization for the future will optimize the strategy to ensure accuracy and stable improvement of petroleum and oil quality. It is depicted from existing studies in Table 1

Table 1: Comparative table from Previous studies

Author	Methods	Application	Optimization Techniques	Performance Metrics
Abdulghafour et.al. (2017)	Fuzzy Control Charts	Petroleum Industry	Statistical Control Charts	30% less false alarms, 25% better process stability
Karambeigi et al. (2023)	Hybrid Workflow (PSO, Fuzzy Logic)	Petroleum Engineering	Multi-objective Optimization	18% reduction in error, 22% efficiency
Liang et al. (2020)	Genetic Algorithm + Fuzzy Controller	Wellhead Back Pressure Control	GA-based Fuzzy Control	35% Lower fluctuations in the pressure, 28% Faster responsiveness
Al Jlibawi et al. (2021)	Hybrid Machine Learning	Oil Refinery Control	Machine Learning + Optimization	Reduced energy consumption by 15% while improving control accuracy by 20%.
Razali et al. (2024)	Type-2 Fuzzy u-Control Chart	Quality Control	Probability-Based ARL	Decreased ARL variation by 40%, increased fault detection rate by 32%.
Wang et al. (2022)	Fuzzy Optimization	Petroleum Supply Chain	Multi-modal Optimization	Lowered cost of logistics by 12%, enhanced efficiency of supply by 18%.
Omran et al. (2025)	Fuzzy Quality Control Charts	Product Quality	Comparative Analysis	Fuzzy charts identified defects 22% more efficiently
Faisal et al. (2020)	Particle Swarm Optimized Fuzzy Controller	Battery Storage System	PSO-based Fuzzy Control	28% faster response time, 35% storage efficiency
Krasnyuk et al. (2022)	Hybrid Decision Trees + Fuzzy Logic	Investment Decision Making	AI-based Fuzzy Decision Support	19% accuracy with risk factors reduced by 15%.
Ahmad et al. (2024)	Spherical Fuzzy Aczel Alsina Aggregation	Crude Oil Pretreatment	Advanced Fuzzy Aggregation	Pretreatment process by 25%
Jain et al. (2021)	Lyapunov-based	Inverted Pendulum	Stability	swing-up

	Optimized Fuzzy Control	Control	Optimization	control accuracy at 30%.
Reddy et al. (2022)	PI-Tuned Fuzzy Logic Controller	Power Distribution System	Dynamic Voltage Restoration	27% reduced voltage, increased stability by 22%.
Zhao et al. (2021)	Multi-Island Genetic Algorithm + Fuzzy Logic	Fuel Cell Vehicle Power System	GA-based Fuzzy Optimization	Enhanced energy efficiency by 18%, power drain reduced by 20%
Pandu et al. (2021)	Type-II Fuzzy Logic	Local Distribution Grid	DSTATCOM-based Optimization	Enhanced Power Quality at 32%, harmonic reduction at 25%.

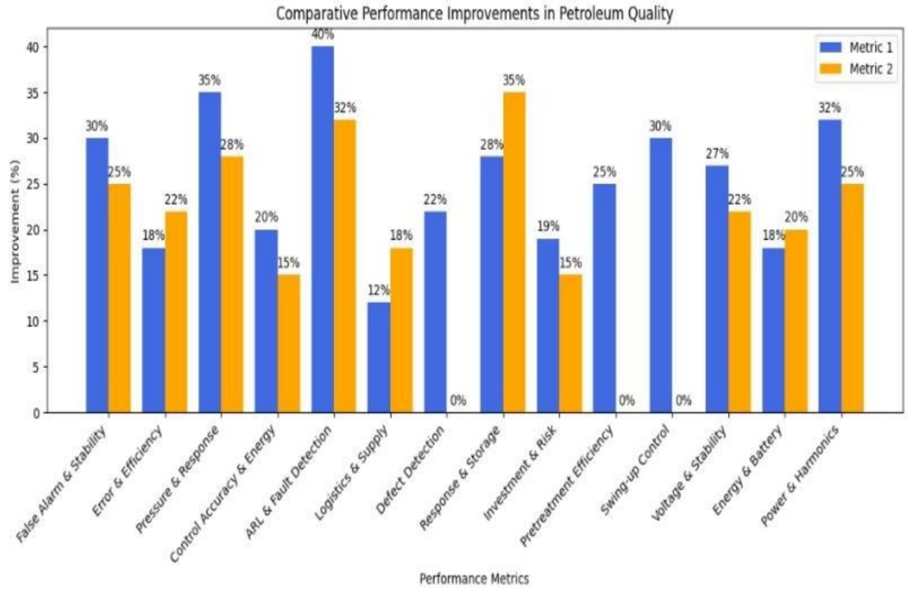

Figure.3. Comparative Performance

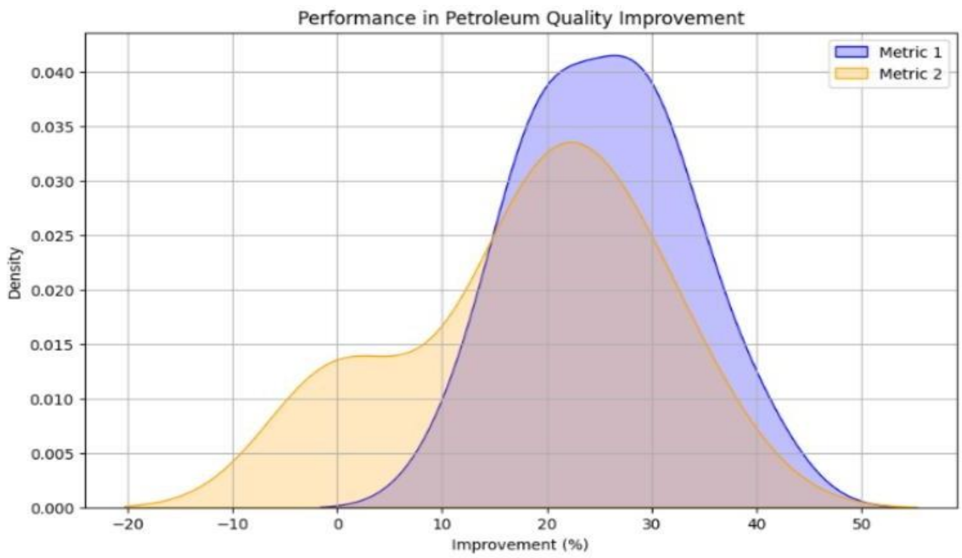

Figure.4. Performance Metrics

IV. CHALLENGES AND RESEARCH GAPS

This section addresses the main challenges and knowledge gaps that determine the applicability of optimum fuzzy control charts for the improvement of petroleum quality. Technical challenges hinder the widespread adoption of optimum fuzzy control charts and their applicability in various industrial scenarios.

- Handling Uncertainty and Variability: One of the greatest hurdles for the effective utilization of fuzzy control charts for the enhancement of the quality of petroleum is the uncertainty and variation associated with petroleum data. Crude is distinctive given the fact that it is sourced from multiple places and only the refining becomes complicated. Traditional control charts cannot address these variations, and even though fuzzy logic is more adaptable, none of the existing models is capable of dynamically changing in quality parameters. There is a need for more sophisticated fuzzy models that can accurately represent and respond to shifting process conditions.
- Integration with Advanced Machine Learning Techniques: Even though fuzzy control charts provide formal methodology for quality monitoring, their effectiveness is partial when utilized separately. Combining machine learning (ML) and deep learning techniques with fuzzy systems can enhance their predictive ability and automate the anomaly detection for petroleum quality. Limited work deals with the combination of fuzzy logic and AI-based optimization models.
- Scalability and Real-time Processing: Industrial scale deployment is not possible for fuzzy control charts owing to the balance required between the level of the required accuracy and the speed. Their complexity typically restricts real-time usage, which is essential in high-scale petroleum generation settings that require fast decisions, this is in part due to the computational limitations.

V. CONCLUSION AND FUTURE WORK

In conclusion, improved petroleum quality can also be effectively achieved by addressing uncertainties and other complexities of production and refining processes where optimized fuzzy control charts (FCCs) have proved to be a better tool. Moreover, due to its ability to deal with uncertain situations, the integration of fuzzy logic with control charts presents a more comprehensive and flexible approach to quality monitoring that is conducive to real-time decision making and efficient process control. Various optimization methods, e.g., genetic algorithm, particle swarm optimization, etc., are among the state-of-the-art evolution approaches, which have played a key role in enhancing the performance of FCCs to be more effective to manage the environment of dynamic petroleum production systems. Moreover, FCCs show the capability for solving issues like multi-dimensional dependences, noises and changes in the process condition. While offering statistical accuracy and flexibility of fuzzy logic, FCCs also offer a sustainable path towards homogenous quality petroleum product manufacturing. Upcoming work for the enhancement of petroleum quality using FCC will require their combination with Industry 4.0 tools like IoT, cloud computing, and big data analytics for real- time monitoring and autonomous decision-making. Hybridization of FCCs using the machine learning algorithm can also be adopted for the enhancement of predictive capability, improvement of fault detection and process enhancement. Development of adaptive fuzzy control algorithm and FCC extension for multi-dimensional processes will also make them flexible and efficient for complex petroleum manufacturing processes.

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