Evaluating the Impact of Fuzzy Logic Controllers on the Efficiency of FCCUs: Simulation-Based Analysis

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***Abstract*—This study investigates the methods for creating nonlinear models and developing Fuzzy logic controllers for the Fluidized Catalytic Cracking Unit (FCCU) at different global refineries. The FCCU plays a crucial role in the petrochemical sector, processing a significant portion of the world's crude oil - in 2006, FCCUs were responsible for refining a third of the global crude oil supply. These units are essential for converting heavier oils, such as gasoil and crude oil, into lighter, more critical products like gasoline and olefinic gases. Given their efficiency in producing a large volume of products and the volatile nature of petrochemical market prices, optimization of these units is a priority for engineers and investors. Traditional control mechanisms often need to improve in managing the FCCU's complex, dynamic, and nonlinear operations, where creating an accurate mathematical model is challenging or involves significant simplifications. Fuzzy Logic controllers, which mimic human reasoning more closely than conventional methods, offer a promising alternative for such unpredictable and complex systems. The results of this work illustrate the usefulness and possible advantages of utilizing Fuzzy Logic controllers in the management of FCCU plants and they are also compared with the latest machine learning techniques as well. These findings are corroborated by simulations conducted with the MATLAB Fuzzy Logic Toolbox R2012b.**

***Keywords*—Non-Linear modeling; fuzzy logic controller; machine learning; optimization**

I. Introduction

Fluidized Catalytic Cracking units are pivotal in petrochemical facilities, transforming dense oil products like Gasoil into lighter, more commercially valuable hydrocarbons. The efficiency of FCCUs significantly influences a refinery's financial performance. These units are comprised of two main components: The Riser reactor, where the cracking of hydrocarbons occurs and catalysts get coated with Coke, diminishing their effectiveness, and the Regenerator reactor, where the catalysts are cleansed and rejuvenated for continuous use. A typical FCCU layout, including key instruments and sections, is illustrated in schematic diagrams. Fuzzy Logic offers a structured approach to handle processes laden with uncertainties, ideal for scenarios lacking precise mathematical models or when existing models are too intricate for swift real-time analysis.

Traditional control systems often fall short in such complex environments [1]. The demand for FCCUs is largely driven by market needs, with seasonal variations in product demand affecting control system design. The challenging nature of FCCUs, characterized by their non-linear, time-invariant, and unpredictable processes, complicates their modeling, simulation, and management. This complexity renders standard controllers, like PID systems, inadequate as they rely on precise plant models, prompting the need for innovative control strategies.

Moreover, FCCUs are crucial for refineries, often determining their profitability and market competitiveness [2]. These units leverage a specialized micro- spheroid catalyst that becomes fluidized under the right conditions, primarily to convert heavy petroleum fractions, known as Gasoil, into valuable products like high-octane gasoline and heating oil. Gasoil, a complex mix of hydrocarbon types, is processed in FCCUS where it is cracked within a riser tube to produce lighter compounds and Coke as a by-product, which subsequently deactivates the catalyst. The spent catalyst is separated, stripped of volatile hydrocarbons, and regenerated by burning off the Coke before being recycled back into the process.

FCCUs have recently included real-time data-collecting systems and other cutting-edge monitoring technology to improve operational effectiveness. These systems make continuous monitoring of critical process variables possible, which gives operators timely insights to enhance performance and make necessary modifications. Additionally, incorporating machine learning and artificial intelligence into FCCU operations has started to yield encouraging outcomes. These tools, which learn from past data and spot patterns that a human operator would overlook, can forecast maintenance requirements, optimize feedstock utilization, and increase overall process efficiency.

Furthermore, under stricter environmental restrictions, refineries are forced to implement more sustainable processes. This entails cutting back on FCCU emissions, especially those of CO_2 and NO_x. Refineries can minimize their environmental impact and sustain high production by refining catalyst regeneration and optimizing the regenerator's combustion process. Another area of active research and development in FCCUs is the introduction of new catalysts that offer improved selectivity towards desired products and are more resistant to deactivation by coke. With these developments, modern refineries hope to strike a compromise between environmental and economic concerns.

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Choosing the appropriate variables is crucial for maximizing FCCU functions. While there is a lot of discussion about the best variables to utilize for fuzzy optimization in FCCUS, this study concentrates on significant variables that can be changed to achieve desired results. These variables fall into one of two categories: dependent-independent or input-output. Feed rate, specific gravity, air flow rate, catalyst circulation rate, cumulative feed rate, and regenerator temperature are significant input parameters. Riser temperature, CO_2/CO ratio, coke deposition on catalyst, feed (gasoil) conversion rate, and the production of LPG and coke are significant output factors. Selection of appropriate variables is a challenging procedure that has a big impact on the outcomes. Previous research in [3] have conducted a thorough review of the variables selected and their effects on FCCU operations.

This study aims to develop and assess complex nonlinear models for fluidized catalytic cracking units (FCCUs). These models aim to increase the petrochemical refining process's operational efficiency and accuracy. The paper highlights the difficulties presented by FCCUs, including their unpredictable nature, time-variant features, and nonlinear behavior. Because these complexities are often too much for traditional control systems to handle, this research focuses on finding crucial input and output factors that significantly impact FCCU performance. The study aims to maximize these variables through fuzzy logic-based control algorithms, providing creative solutions that improve refinery profitability and market competitiveness while addressing environmental issues.

II. Methodology

Prior to adopting Fuzzy Logic, scientific inquiries were predominantly confined to mathematical models tailored for FCC units [4]. These models varied in their level of detail and accuracy. Research often revolved around comparing these models to discern their respective strengths and weaknesses. Given the critical role of FCCUs in both industrial and market contexts, research in this area has been extensive, covering aspects such as stability, optimization, and the development and simulation of mathematical models [5]. Comprehensive reviews have been conducted on the evolution of FCCU control strategies over time. Notably, there has been considerable research focusing on the safe operation of FCCUs. Fig. 1 illustrates the basic structure of a Fluid Catalytic Cracking Unit.

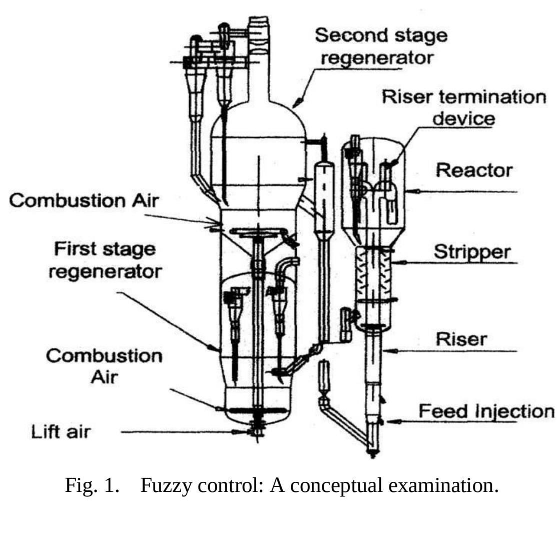

Fig. 1. Fuzzy control: A conceptual examination.

Initial studies indicated that Fuzzy Logic models outperformed traditional statistical methods in identifying process characteristics. Efforts were made to apply linear regression and sophisticated Kalman filtering techniques to improve precision, yet these methods struggled to accurately represent and manage real-world plants due to their inherent nonlinearity, vagueness, and unpredictability. Consequently, alternative strategies, including Neurofuzzy systems and genetic algorithms, began to gain traction. Despite advances in modern control methodologies like parameter estimation and stochastic and optimal control for model identification, the complexity of some industrial processes, characterized by high nonlinearity and uncertainty, defies conventional mathematical modeling and control approaches [6]. Fuzzy Logic, with its capacity to handle dynamic, nonlinear, and imprecise scenarios through linguistic rules, emerges as a suitable solution for such complex systems, commonly found in sectors like petrochemicals, nuclear energy, and water treatment. In situations when processes are well understood at the microscopic level, rigid control approaches are used.

However, standard control procedures often fail to provide satisfactory solutions to industrial issues contaminated by poor mathematical models. Artificial neural networks and fuzzy logic, two facets of soft computing that have recently found their way into the industrial control area, were originally applied in fuzzy control [7]. Product quality, efficiency, and energy consumption have all significantly improved as a result of this technology's application across a range of sectors [8]. Nowadays, fuzzy control is recognized as a state-of-the-art, complex control technique. Fuzzy logic and neural networks are increasingly being combined in scientific study, placing intelligent control front and center, particularly for systems whose parameters can be adjusted to conform to language conventions [9]. The two primary objectives of this research are to find the nonlinear relationships between input and output variables and to design a robust optimization framework with the aim of lowering Coke deposition on the catalyst and boosting LPG output and gasoil conversion.

A. *Fuzzy Control: A Conceptual Examination*

Fuzzy Logic mirrors the decision-making process of human experts, making it inherently user-friendly for both technical and non-technical applications. Its outputs, often described using everyday terms like "cold," "hot," or "fast," are straightforward and require little to no additional interpretation [10]. The development of a Fuzzy Logic system relies on the expertise and knowledge of specialists, who formulate this knowledge into a set of rule-based instructions for creating databases and Fuzzy rules. These rules, while approximate, reflect the inherently imprecise nature of human decision-making.

In practice, a Fuzzy rule-based system (FRBS) combined with a de-fuzzification component can serve as a stand-in for a human expert. This system takes in precise sensor data, translates these concrete values into heuristic variables using defined membership functions, and processes these variables through IF-THEN rules. The system then converts these linguistic variables back into a precise numerical output during the de-fuzzification stage, offering an estimated value close to the desired output [11].

A significant advantage of Fuzzy Logic is its independence from in-depth knowledge of the underlying system or its internal processes, a flexibility not typically found in traditional control systems like PID controllers. A schematic representation of a Fuzzy Logic controller would include the rule-based system, which stores the control strategy in rule format, the inference mechanism, which applies these rules based on current conditions to determine appropriate inputs; the fuzzification interface, which prepares the inputs by aligning them with the system's rules [12]; and the de-fuzzification interface, which translates the system's conclusions into actionable inputs for the system. In Fig. 2, Standard Fuzzy Logic Controller Architecture is mentioned.

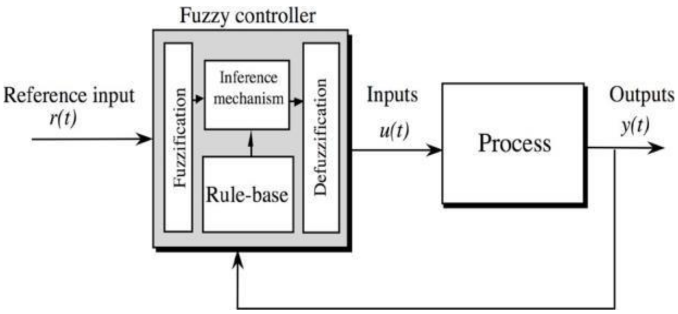

Fig. 2. Standard fuzzy logic controller.

B. Fuzzy Modeling of FCCU

1) Choosing variables: Parameters for Inputs andOutputs: This research utilizes data sourced from the operational guides and technical materials of different refineries across the world. Owing to the absence of a mathematical framework, a rule-based Fuzzy methodology was adopted for modeling. The process involved identifying key operating parameters of the FCCU as inputs and outputs, which represent the independent and dependent factors respectively [13]. The input variables in this study were selected based on their influence on the effectiveness and functionality of fluidized catalytic cracking units (FCCUs). Feed rate, specific gravity, airflow rate, catalyst circulation rate, cumulative feed rate, and regenerator temperature are among the chosen input factors. These variables, which include gasoil conversion rate, liquefied petroleum gas (LPG) generation, and coke deposition on the catalyst, were essential elements that directly affect the performance and output of the FCCU.

These factors were chosen because they regulate and enhance the cracking process. For example, the unit's throughput is determined by the feed rate and the rate at which the catalyst circulates, and the maintenance of the intended reaction conditions depends on the specific gravity and temperature of the regenerator. The airflow rate to the regenerator is an essential control parameter since it affects the combustion process and, in turn, the catalyst's regeneration.

A list provided in Table I outlines 16 critical parameters in the FCCU operation, categorizing them into control and observed variables. The Fuzzy controller is tasked with mapping out the behavior and interconnections of these variables through the creation of dynamic nonlinear representations, referred to as surface graphs. Based on their significance and impact within the FCCU process, a selectionof six inputs and six outputs was made for focus [14]. To enhance the refinery's efficiency, both control and observational variables were pinpointed, with continuous monitoring of Riser and Regenerator temperatures. Adjustments to the Catalyst feed and air supply rates, serving as control variables, are made to fine-tune the process parameters towards the targeted outcomes [15].

TABLE I. INPUT AND OUTPUT SPECIFICATIONS FOR FUZZY LOGIC SYSTEM

Input Variables	Output Variables
Gasoil (Feed)	C02/CO
Catalyst Recirculation Rate (CRR)	Gasoil Conversion Rate (GOCR)
Regenerator Temperature (RET)	Liquefied Petroleum (LPG)
Airflow to Regenerator (ATR)	Riser Temperature (RIT)
Cumulative Feed Rate (CFR)	DCC
Specific Gravity Factor (SG)	Coke as Bypass Product (Coke)
Control Variables	Observed Variables
Recycled Catalyst Rate	Riser Temperature
Airflow Rate	Regenerator Gas Temperature

2) Design of a fuzzy logic controller for FCCU: To develop the rule-based Fuzzy system that processes the nonlinear relationship between inputs and outputs, six essential steps are followed:

a) Determine the inputs, define their boundaries, and assign labels to them.

b) Specify the outputs, outline their boundaries, and label them accordingly.

c) Establish degrees of truth through Fuzzy membership functions.

d) Construct the Rule base necessary for the design of the controller.

e) Allocate intensities to the rules and define how they interact with each other.

f) Integrate the rules and convert the Fuzzy output into a crisp value through defuzzification [16].

Table II also presents the clustering of data for membership functions. To compile the knowledge base and establish rules, insights were obtained from a seasoned Process Engineer and a Senior Instrumentation Engineer active in the facilities. These rules were formulated based on operational manuals and various technical materials provided by the licensing authorities.

TABLE II. VARIABLES CLUSTERING RANGES

Clustering Group	Equivalence
Low	Small Impact
Medium	Steady State
High	High Impact

Tables III and IV present the initial values for both input and output variables, accompanied by their respective ranges. The membership functions were defined within these specific ranges.

TABLE III. CLUSTERING RANGES FOR INPUT VARIABLES

Input Variables	High (H)	Medium (M)	Low (L)
ATR (m3/h)	39,451 - 60,167	27,001 -47,209	0 - 29,873
RET (°C)	630 – 670	575 - 645	0 - 610
SG (-)	0.668 - 0.878	0.452 - 0.796	0 - 0.660
CFR (m3/d)	2,289 – 2,650	2,011 – 2,450	0 – 2,260
CRR(t/min)	14.9 – 16.9	11.2 – 16.1	0 – 15.2
Gasoil (m3/d)	1,967 – 2,250	1,770 – 2,151	0 – 1,980

TABLE IV. CLUSTERING RANGES FOR OUTPUT VARIABLES

Output Variables	High (H)	Medium (M)	Low (L)
CO2/CO (mol/mol)	2.2 – 6.2	0.9 – 3.9	0 – 1.8
DCC (-)	0.753 – 0.980	0.397 – 0.865	0 – 0.791
RIT (°C)	505 – 528	404 – 520	0 – 479
LPG (wt.%)	19.5 – 30.9	14.3 – 21.8	0 – 18.5
GOCR (wt.%)	79.3 – 98.16	44.9 – 93.8	0 – 76.8
Coke (wt.%)	5.2 – 9.1	3.4 - 7.5	0 – 4.2

This study chose triangular functions due to their ease of use and effectiveness in modeling fuzzy sets. These features aid in reducing computational complexity, which is essential for FCCUs and other real-time control systems. Triangle functions are perfect for situations where prompt responses are required, like in refining operations where precise control is required to maintain process stability and maximize output because of their linear nature.

3) Detailed description of fuzzy rules: The rules that connect the input and output variables are listed below. These rules were implemented using the MATLAB Fuzzy Rule Editor to generate the inference and nonlinear surface model.

In Fuzzy control systems, the focus is on utilizing linguistic rules, whereas traditional control systems rely heavily on differential equations. Employing verbal rules aligns more closely with human understanding than does a numerical approach [17]. Within a Fuzzy logic framework, these rules are always applicable but vary in their degree of truth from zero to one. The initial step of the inference process involves verifying the applicability of the rule premises for the given situation [18]. If the premises meet the criteria, the corresponding rules are chosen in a phase commonly referred to as "Matching." Following this, the inference system proceeds to make decisions.

The membership function for Specific Gravity (SG), a crucial statistic that represents the nature and quality of the feedstock entering the FCCU, is shown in Fig. 3. The SG membership function categorizes the feedstock according to its density, enabling the fuzzy logic controller to adjust the processing parameters to suit the feedstock's properties better. This classification may optimize the cracking process to provide the required product yield by modifying factors like temperature and catalyst activity. The system's entire operating efficiency and product quality can be improved by efficiently regulating the SG of the input.

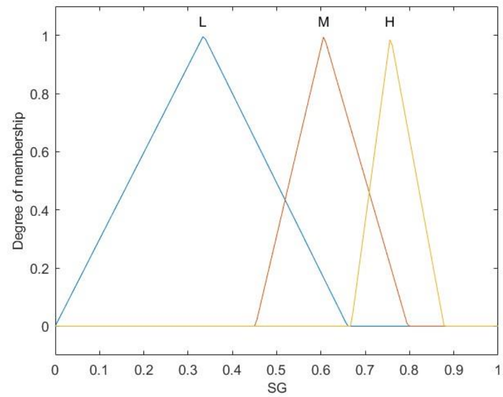

Fig. 3. SG Membership Function.

1-If (SG is H) then (LPG is M)(GOCR is H)
2-If (SG is H) then (Coke is H)(CO2/C0 is H)
3-If (SG is H) then (DCC is M)(RIT is L)
4-If (SG is L) then (CO2/C0 is L)
5-1f (SG is L) then (RIT is H)
6-If (ATR is H) then (Coke is H)
7-If (ATR is H) then (RIT is M)(CO2/C0 is M)
8-If (ATR is M) then (CO2/C0 is M)
9-If (ATR is M) then (DCC is L)
10-If (ATR is M) then (Coke is M)
11-If (ATR is L) then (CO2/C0 is L)
12-1f (ATR is L) then (DCC is M)
13- If (RET is H) then (RIT is M)(CO2/C0 is L)
14- If (RET is H) then (DCC is H)(LPG is M)(GOCR is L)
15-If (RET is H) then (Coke is M)(DCC is H)
16-If (RET is H) then (RIT is H)
17-1f (RET is M) then (Coke is M)(LPG is M)(GOCR is H)
18-If (RET is M) then (CO2/C0 is M)
19-1f (RET is M) then (Rh T is H)
20-If (RET is M) then (Coke is M)
21-If (RET is L) then (RIT is M)
22-1f (RET is L) then (DCC is L)
23-If (RET is L) then (CO2/C0 is L)
24-1f (RET is L) then (Coke is L)
25-If (RET is L) then (LPG is M)(RIT is L)(GOCR is L)
26-If (CFR is H) then (RIT is M)(GOCR is M)
27- If (CFR is H) then (DCC is L)(LPG is H)(RIT is M)(GOCR is H)
28- If (CFR is M) then (DCC is M)(LPG is M)(RIT is M)
29-If (CFR is L) then (DCC is M)(LPG is L)(GOCR is H)
30- If (CRR is H) then (Coke is M)(RIT is H)(GOCR is L)(CO2/C0 is H)
31- If (CRR is M) then (Coke is M)(GOCR is M)
32-If (CRR is L) then (Coke is L)(GOCR is M)

33- If (Gasoil is H) then (RIT is M)(GOCR is L)(CO2/C0 is L)
34- If (Gasoil is M) then (GOCR is M)
35-If (Gasoil is L) then (GOCR is H)

The numerical value of specific gravity is calculated by dividing the density of the substance being measured with the density of the reference. The reference substance is nearly always water at its densest (997 kg/m^3).

The membership function for Differential Coke Concentration (DCC), a crucial variable in the management of Fluidized Catalytic Cracking Units (FCCUs), is shown in Fig. 4. The concentration of coke created during the cracking process is divided into three categories by the DCC membership function: low, medium, and high. Because of this classification, the fuzzy logic controller may effectively manage the regeneration process, which can modify temperature and airflow to maintain the best possible catalyst performance. The system can better regulate coke deposition by identifying these categories essential for preserving efficiency and reducing downtime in FCCUs.

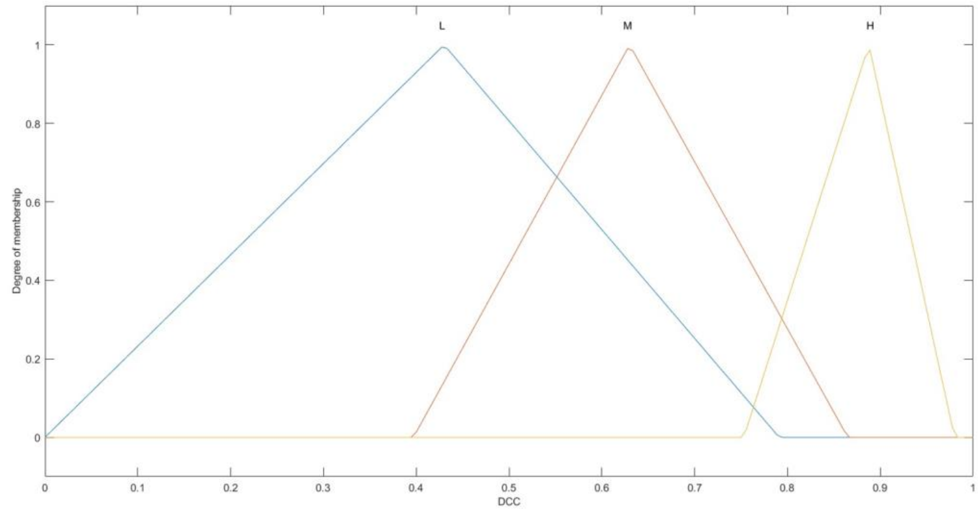

Fig. 4. DCC Membership Function.

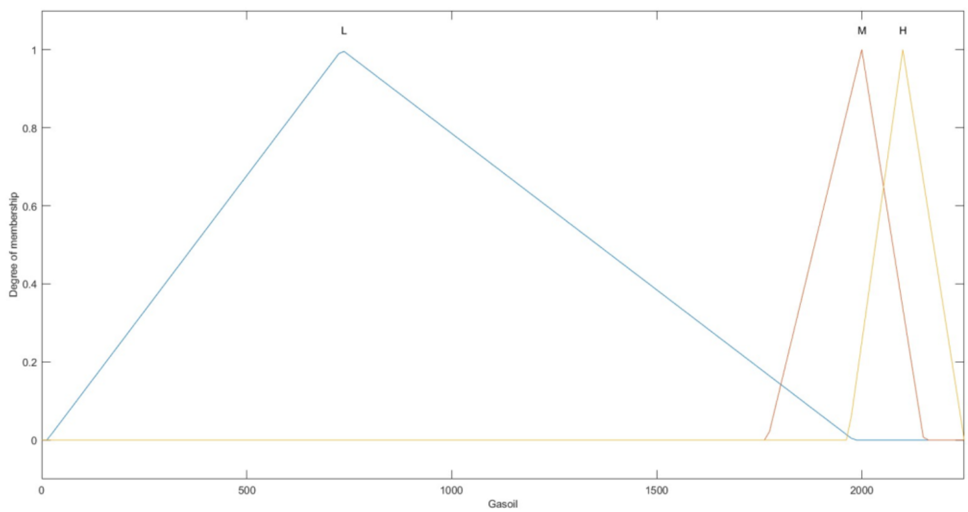

Fig. 5. Gasoil membership function.

The membership function for Gasoil, a crucial input variable in FCCUs, is shown in Fig. 5. The fuzzy logic controller can modify the processing conditions by dividing the input feedstock into distinct ranges based on the Gasoil membership function. The system can maximize conversion efficiency and minimize the creation of undesirable byproducts by classifying Gasoil into low, medium, and high levels during the cracking process. Maintaining the proper ratio between feedstock input and the intended output of lighter hydrocarbons, such as gasoline and LPG, depends on this function.

The membership function for the CO2/CO ratio, which is essential for tracking the regenerator's combustion efficiency inside the FCCU, is seen in Fig. 6. The fuzzy logic controller can modify the airflow and combustion parameters to maximize catalyst regeneration because the CO2/CO membership function divides the ratio into several regions. To guarantee that the coke on the catalyst is efficiently burnt off without producing too many emissions, the CO2 and CO levels must be in the right balance. Maintaining both operational effectiveness and compliance with environmental standards depends on this role.

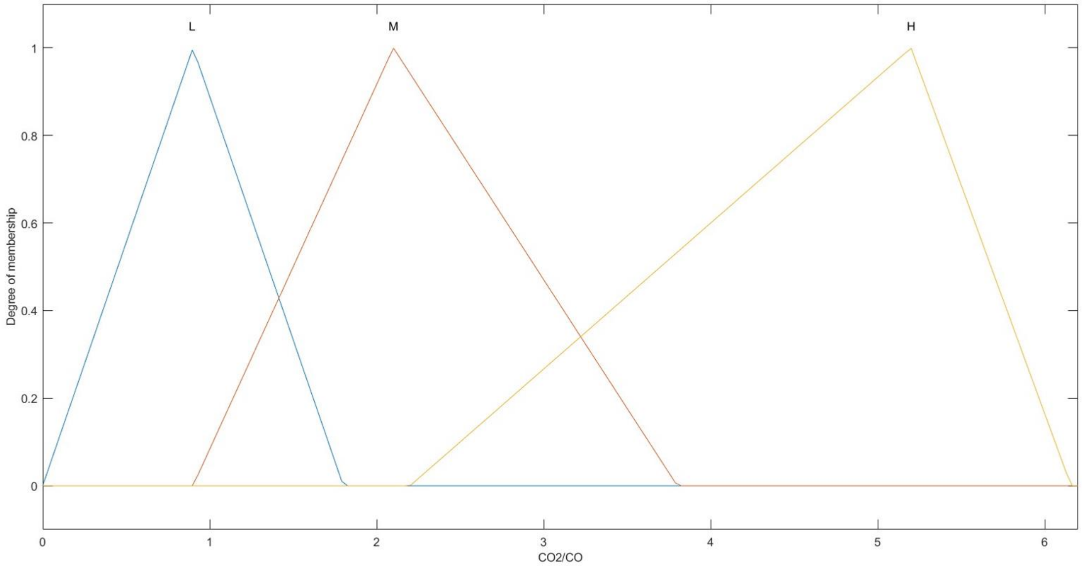

Fig. 6. CO2 / CO membership function.

4) Defuzzification: The final step in the Fuzzy control process involves defuzzification, where the Fuzzy controller converts the Fuzzy output into a precise control signal. This signal is then applied to the system by adjusting the relevant variables. During this stage, the inference system identifies the most definitive scenario and generates the output based on it [19]. The goal of defuzzification is to translate the Fuzzy decision- making process into a clear, actionable control measure that accurately reflects the range of potential outcomes [20]. The Fuzzy surface chart is an invaluable tool, offering insights into the relationship between the input and output variables, how quickly the system responds to input variations, and the direction in which these changes occur [21]. This information provides engineers with a novel approach to plant analysis, offering perspectives that traditional control strategies cannot offer [22]. Being able to test multiple alternative outcomes at once without having to deduce the system's mathematical formulas is incredibly helpful.

III. Results and Discussion

Although conventional control methods have proven successful in resolving many mathematical problems in the field, their shortcomings when handling intricate, dynamic settings have brought to light the benefits of Fuzzy Logic for control engineers confronting these kinds of problems. Fuzzy Logic relies on the experience of seasoned experts in the subject rather than Ordinary Differential Equations (ODEs). The Neuro Fuzzy technique, which is gaining traction and seems to have a lot of potential for future applications, is the result of the growing interest in enhancing Fuzzy Logic with experiential learning.

In order to create Fuzzy Logic models and control designs, this study made use of data from technical literature and operational manuals. The MATLAB Fuzzy Logic Toolbox 2012b was utilized to apply this data, and Fig. 7 through 10 present the main conclusions. Fuzzy Logic enables the avoidance of intricate mathematical calculations, necessitating instead the profound comprehension and discernment of an accomplished professional. Previously, a Yokogawa Distributed Control System (DCS) was used to operate the facility in question. This system implemented rules through specialized programming, which required manual modifications during maintenance or transitions. The study's data precision is in close agreement with the operational data of different facilities, which was collected in 2004 and may not be representative of the current operating conditions. Though areas like CRR and CFR required more tweaks for optimal performance, the fuzzy control model established via this study indicated good performance, with certain conclusions fitting well with real operational data.

Finishing the facility's fuzzy model provides a wealth of information. The linear relationship between the ATR variable and Coke output, for instance, is depicted in Fig. 7, where production increases directly up to a certain point and then declines as the ATR variable rises further, peaking at an ATR of 54,000. The utilization of numerical optimization techniques to increase facility efficiency is made easier by this pattern recognition. Furthermore, as seen by the 3D depiction in Figure 9, the study demonstrates the effectiveness of Fuzzy Logic in producing three-dimensional outputs that are on par with PID controllers, particularly when managing intricate and unexpected systems like FCCUs. More applications of fuzzy logic are shown in Fig. 8 and Fig. 10, which also offer more insights into the advantages of fuzzy logic for industrial process improvement.

A comparison of the suggested fuzzy logic control method with current FCCU management techniques is shown in Table V. It emphasizes how the fuzzy logic approach, which does not primarily rely on intricate mathematical models, provides greater flexibility and effectiveness in managing the intricate, nonlinear dynamics of FCCUs. The table also shows how this methodology performs better than alternative approaches in streamlining operations, decreasing coke deposition, and raising LPG output.

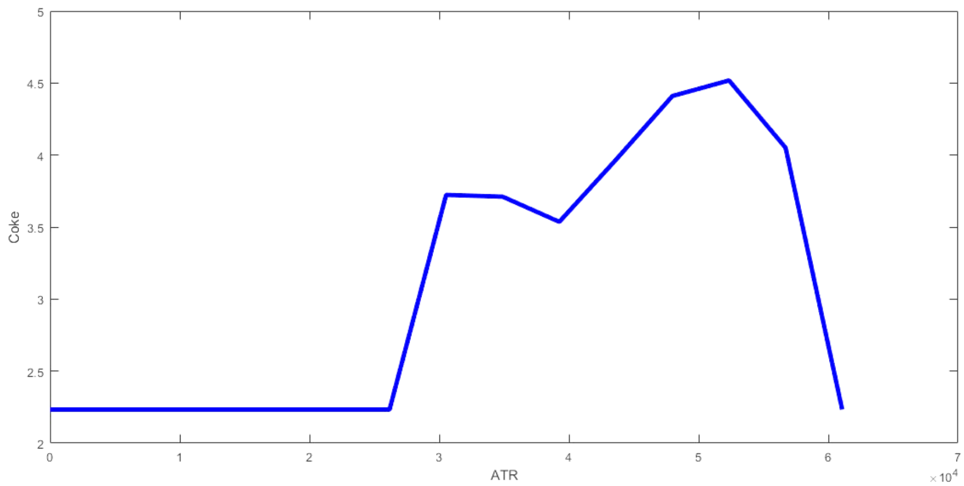

Fig. 7. Coke production according to ATR only.

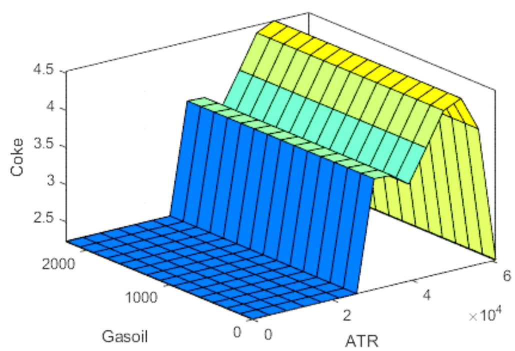

Fig. 8. Coke production according to Gasoil and ATR

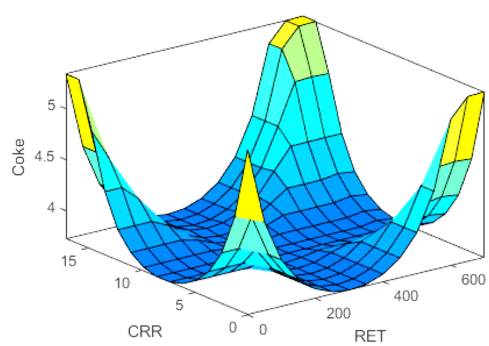

Fig. 9. Coke Production according to CRR and RET

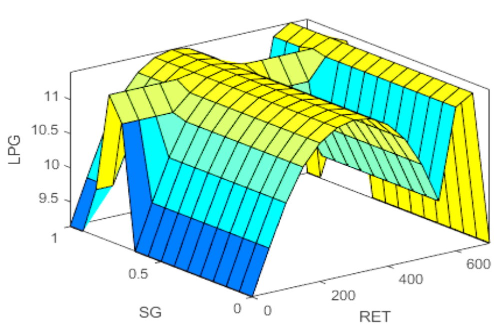

Fig. 10. LPG production according to SG and RET.

TABLE V. COMPARISON WITH EXISTING SOLUTIONS

Feature	Proposed Work	Acosta-López & de Lasa et al. [4]	Hu & Zhou et al. [5]	Nan Liu, Chun-Meng Zhu et al. [6]	Tianyue & Long et al. [7]	Tian and Wang et al. [8]
Control Approach	Utilizes fuzzy logic for adaptive response to FCCU dynamics.	Integrates CPFD with ML for predictive modeling.	Optimizes GCS and ASS using Aspen Plus simulation.	Uses CNN-based adaptive framework for optimization.	Bilevel robust optimization for handling uncertainties.	ML for early warning of abnormal conditions
Efficiency in Handling Complexity	Manages nonlinear operations without precise mathematical models.	Handles complex FCCU variables with high predictive accuracy.	Reduces utility costs and improves operational efficiency.	Addresses complex, multivariate nature of FCC processes.	Improves robustness and performance under uncertainty.	Improves safety and stability with early warnings.
Adaptability	High adaptability due to rule-based nature.	High adaptability using hybrid models.	Adaptive to varying operational parameters.	Adaptive to complex and dynamic FCC conditions.	Adapts to uncertain operational conditions.	Adapts to changing operational conditions.
Dependence on Mathematical Models	Does not rely on detailed mathematical models.	Uses CPFD simulations combined with ML.	Utilizes process simulation software for optimization.	Combines CNN with process models for better control.	Uses data-driven models to handle uncertainties.	Uses ML for predictive maintenance.
Performance	Optimizes operations with reduced coke deposition and increased LPG output.	High predictive accuracy with CPFD-ML integration.	Significant cost savings and efficiency improvements.	Enhances FCC performance with adaptive frameworks.	Improves FCC performance with robust optimization.	Effective early warning system for abnormal conditions.
Future Improvements	Refine rules and employ numerical optimization.	Further integration of CPFD and ML for enhanced accuracy.	Extend to other FCC subsystems for comprehensive optimization.	Enhance adaptability with more complex models.	Further improve robustness with additional data.	Improve early warning algorithms with more data.

IV. CONCLUSION

This study provides compelling evidence of the efficacy of the fuzzy logic approach in producing accurate findings in dynamic and nonlinear settings. The inherent unpredictability and nonlinearity in petrochemical facilities, notably in Fluid Catalytic Cracking Units (FCCUs), proved to be a perfect fit for this method. The fuzzy controller designed to handle the complexity of FCCUs worked exceptionally well, demonstrating its potential as a dependable control method in these demanding situations.

However, it is essential to recognize the limitations of this study. First, there is a need for improvement in the accuracy of the membership functions and fuzzy rules. Even though the existing configuration produced good results, performance may be improved by expanding the collection of rules and improving precision. Second, much of the study's data came from simulations and historical operational records, which might not accurately reflect the subtleties of operational dynamics in real-time. To improve the fuzzy logic controller's resilience, further in-the-real-world testing and the addition of real-time data should be done in subsequent research.

Furthermore, a viable path for future development is incorporating sophisticated control approaches like Artificial Intelligence (AI) and Neuro-Fuzzy systems. These methods can offer more intelligent and adaptable control mechanisms, improving FCCU dependability and overall performance. In the end, these systems' ongoing development will be essential for streamlining processes and ensuring they successfully address environmental and economic concerns.

Lastly, a crucial component of FCCU activities is resolving environmental issues. Future studies should investigate how AI and fuzzy logic might optimize the process to use less energy and produce fewer pollutants. One way is to create control systems that reduce CO2 and NOx emissions while preserving high productivity levels. Refineries can strengthen their competitive advantage in a market where environmental responsibility is becoming increasingly crucial by integrating their control system with sustainability goals.

AUTHORS' CONTRIBUTION

The first author, Harsh Pagare, was the main contributor to the study's conceptualization by creating the research framework and the fuzzy logic controllers. His primary responsibilities were interpreting and analysing the findings based on the simulation. He also made a significant literary contribution to the manuscript, helping to ensure that the research findings were well-expressed and backed up by solid data.

The second author, Kushagra Mishra, played an equally important role in conceptualising and developing the fuzzy logic controllers. He led the development and perfecting of simulation models and research techniques. Kushagra was also closely involved in the data gathering, processing, and interpretation processes to guarantee the precision and dependability of the results.

The third author, Kanhaiya Sharma, concentrated on the implementation's technical details, especially optimising the Fuzzy Logic system in MATLAB. In addition, he helped with the technical composition of the manuscript, the final review, and editing. He also contributed to data analysis.

The fourth author, Sandeep Singh Rawat, helped the team refine the study strategy and offered insightful feedback throughout the simulation phase. He helped with the data validation process and reviewed the literature, among other things.

The fifth author, Shailaja Salagrama, helped with the theoretical framework and made sure the study followed scholarly guidelines, which were two ways she contributed to the research. She also contributed to the Research Paper's final review and proofreading.

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