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REVIEW

Applications of Artificial Intelligence in the Fluid Catalytic Cracking Process in Petroleum Refineries

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Abstract: In recent decades, the petroleum industry has faced numerous challenges such as crude oil price fluctuations, increasing demand for high-value products, and stricter environmental regulations. The Fluid Catalytic Cracking (FCC) unit, considered the heart of a modern refinery, plays a crucial role in converting heavy petroleum fractions into high-value products such as gasoline, diesel, and liquefied petroleum gases. Optimizing the performance of this unit not only increases profitability but also reduces energy consumption and pollutant emissions. Recent advances in artificial intelligence (AI), particularly in artificial neural networks, deep learning, and deep reinforcement learning, have provided unique opportunities to enhance efficiency, sustainability, and operational safety in refineries. This paper reviews the application of these advanced AI techniques in the optimization and control of fluid catalytic cracking units and discusses current challenges and future perspectives.

Keywords: artificial intelligence, fluid catalytic cracking, neural network

1 Introduction

The Fluid Catalytic Cracking (FCC) process is one of the most vital and complex units within any modern oil refinery. It serves as the backbone of gasoline and other valuable light hydrocarbon production. The primary objective of the FCC unit is to convert heavy, low-value fractions of crude oil—such as heavy gas oils and vacuum distillation residues—into lighter products that are in greater demand, such as high-octane gasoline, liquefied petroleum gas (LPG), and olefins (feed-stocks for petrochemical plants). The importance of FCC stems not only from its high gasoline yield but also from its flexibility in responding to market fluctuations and feedstock quality. In this process, the heavy feedstock comes into contact with a finely powdered catalyst inside a reactor operating at elevated temperature and pressure. The catalyst, generally composed of zeolites, facilitates the cracking reactions of large hydrocarbon molecules. These reactions occur rapidly and produce a wide range of products. After the reaction, the catalyst is separated from the products and sent to the regenerator, where the accumulated coke is burned off and its activity is restored. Precise control of temperature, pressure, catalysttooil ratio, and contact time is crucial for performance optimization and for maximizing valuable yields, an area in which AI plays an increasingly important role [1–7]. (see Figure 1)

The dynamic and complex nature of the FCC process makes it an ideal field for advanced AI applications. In recent years, the emergence of AI and machine learning has enabled more accurate process behavior prediction and the development of automated and adaptive control strategies. These tools can construct complex models beyond purely physics-based approaches. Machine learning aids in pattern analysis and predictive modelling; artificial neural networks (ANNs) model non-linear processes; genetic algorithms optimize process parameters; fuzzy systems manage uncertainty in data and decision-making; and Monte Carlo simulations estimate the likelihood of different operational scenarios—each of which is considered a key AI technique in petroleum process applications [8–11]. In the following sections, specific AI techniques and their applications in FCC units are explored in detail.

2 Artificial Neural Networks (ANN) in FCC

Artificial Neural Networks represent a class of computational models inspired by the structure and learning mechanisms of the human brain. Each network is mathematically represented

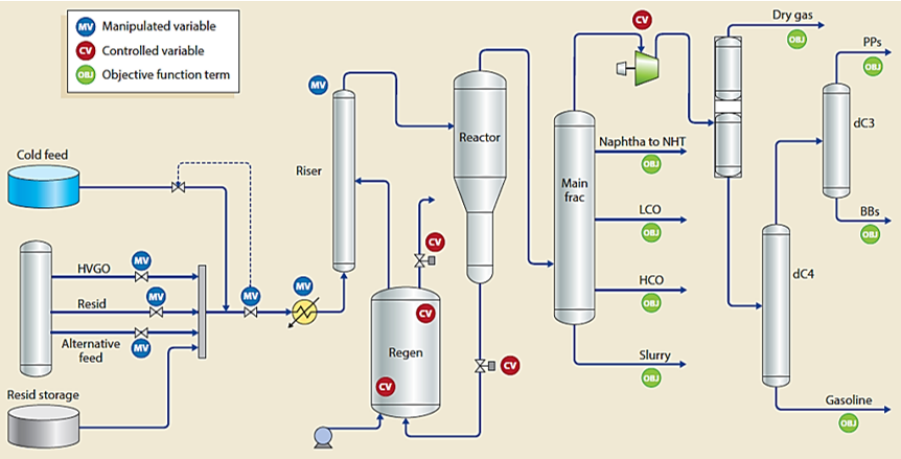

Figure 1 Schematic of a refinery FCC unit, key variables, and objective functions for process control

by a graph consisting of adjustable parameters, commonly known as "weights." Through training algorithms, these parameters are iteratively optimized to reproduce desired system behavior. The learning process in biological neurons also relies on strengthening or weakening connections, modelled mathematically by adjusting the weights of the network. Applications of AI in industrial process optimization and control have dramatically expanded in recent years. Among them, ANNs have demonstrated exceptional capability in modelling non-linear, complex systems, making them highly suitable for predicting key operational parameters and product quality in FCC units. Their ability to learn from historical data and generalize to unseen conditions makes them an ideal solution for various refinery applications. Such parameters may include temperature and pressure across reactor and regenerator sections, feed flow rate, catalysttooil ratio, and quality indicators of products such as gasoline octane number and diesel boiling range [12]. (see Figure 2)

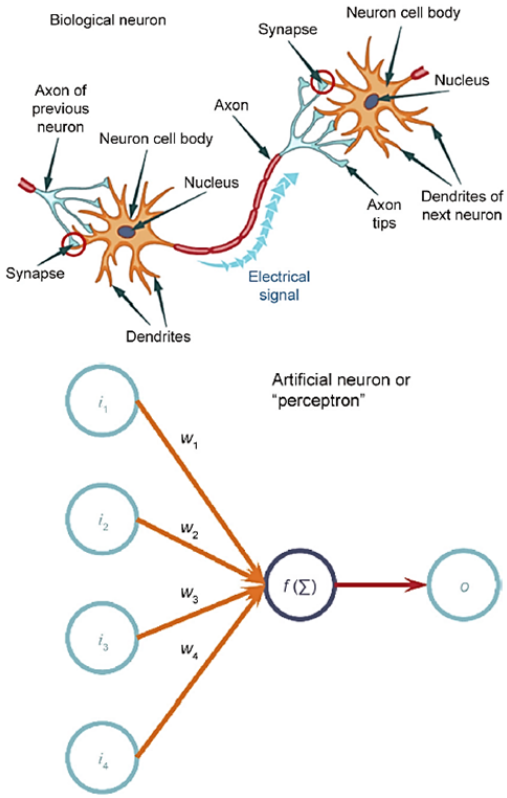

Figure 2 Biological Neural Network vs. Artificial Neural Network (i: inputs; w: weights; o: output; f(Σ): activation function)

Studies have shown that ANNs can predict critical outputs such as gasoline yield, octane number, and coke formation with significant accuracy, thereby supporting real-time decision-making. Improvements in yield achieved through ANNbased optimization have been reported to reach up to 1.5%. Beyond prediction, ANNs also play a vital role within Model Predictive Control (MPC) frameworks—advanced controllers used in industrial processes that incorporate system constraints during real-time optimization. Using an ANN model to predict process dynamics enables MPC to design control actions that meet performance targets while adhering to physical limitations. This results in more precise, stable control of FCC units even under disturbances [13–15]. (see Figure 3)

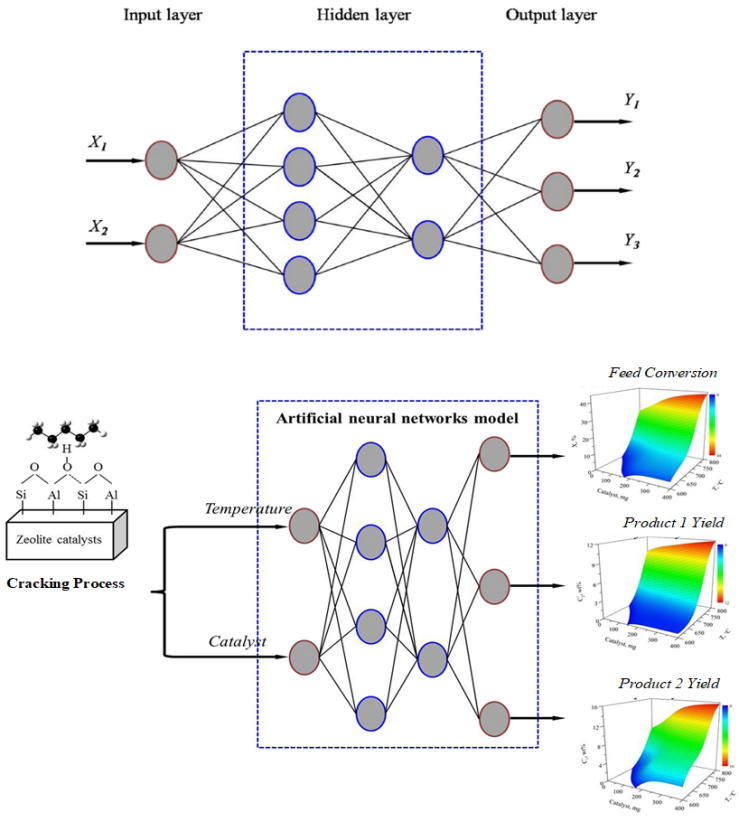

Figure 3 Example pattern of Artificial Neural Networks in FCC process simulation

By optimally adjusting temperature and pressure according to ANN predictions, refineries can maximize valuable product yields and minimize undesirable by-products. Furthermore, ANNs can rapidly assess the quality of the gasoline product, particularly octane numbers (RON/MON), allowing operators to maintain product specifications within desired limits—directly enhancing refinery profitability [16].

In a reported case study, an Ann-based control system was implemented to optimize gasoline yield in an FCC unit. Trained on historical process data, the ANN modelled the relationship between input parameters (temperature, pressure, feed flow rate, and feed quality) and output parameters (gasoline yield and coke formation). The system successfully predicted feedstock variations and suggested optimal settings for controllable parameters. Results indicated a gasoline yield improvement of approximately 1.5%, demonstrating the power of Ann-driven prediction and real-time optimization [1, 17].

3 Deep Learning (DL) and Deep Reinforcement Learning (DRL) in FCC

Deep Learning (DL) is a sub-field of machine learning that enables computational models to automatically learn complex patterns and features from large and diverse datasets. By utilizing multi-layered neural networks, DL creates a structure akin to the human brain that is capable of processing data across multiple abstraction levels to identify underlying patterns. In simple terms, DL allows computer systems to perform learning autonomously, with minimal human

intervention. DL builds on Artificial Neural Networks (ANNs), which are inspired by the function of the human brain. These networks consist of small computational units called "neurons." Every network comprises three main types of layers:

(1) **Input Layer:** Raw data from the environment (e.g., images, text, or sound) enters this layer.

(2) **Hidden Layers:** Positioned between the input and output layers, these layers are where the actual learning takes place. Each neuron in these layers receives various inputs, processes them, and passes the result to the next layer.

(3) **Output Layer:** This layer provides the final result that the network produces (e.g., the class of an object in an image or a forecast numerical value).

Reinforcement Learning (RL) is another AI paradigm where an agent interacts with an environment and learns optimal actions through a system of rewards and penalties. When RL is combined with DL, the result is Deep Reinforcement Learning (DRL), meaning the agent uses deep neural networks to understand the environment's state and inform its decision-making. While ANN forms the basis for many AI applications in the industry, DL, and particularly DRL, represent advanced steps that unlock new possibilities for optimizing and controlling FCC units. DL, as a branch of ANN featuring multiple hidden layers (Deep Neural Networks), is capable of extracting more complex and abstract features from massive datasets. This capability makes it suitable for more accurate modelling of catalyst behavior and intricate chemical processes within the FCC. For instance, Deep Neural Network (DNN) models can be employed to predict catalyst activity, deactivation rates, and the impact of feedstock composition on catalyst performance. These predictions aid in better decision-making regarding catalyst replacement schedules and the optimization of catalyst consumption [18–20].

3.1 Catalyst Activity Modelling and Prediction with DL

The application of DL in predicting the activity and lifespan of FCC catalysts has also been explored. A deep learning model was trained using extensive data covering catalyst characteristics, feedstock composition, and operational conditions to predict the catalyst deactivation rate and its remaining activity. This model assisted the refinery in determining the optimal timing for catalyst replacement or fresh addition with greater precision. Results indicated that the use of this DL model led to a 5% to 10% reduction in catalyst consumption while maintaining unit performance. This highlights DL's ability to extract complex patterns from large datasets and model challenging physicochemical phenomena, thus improving resource management and reducing operational costs [21]. (see Figure 4)

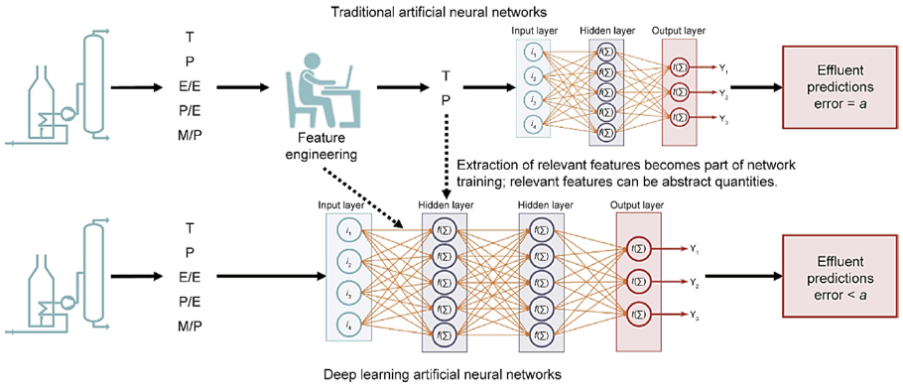

Figure 4 Comparison of ANN and DL structure applications in an FCC unit (T: temperature; P: pressure; E/E: the product ratio of ethylene to ethane; P/E: the product ratio of propylene to ethylene; M/P: the product ratio of methane to propylene; Y1: output 1; Y2: output 2; Y3: output 3; a: certain value; t(Σ): activation function)

DRL is a more advanced approach that merges DL with Reinforcement Learning. In DRL, an intelligent agent learns to make optimal decisions over time by interacting with the environment (the FCC unit). This agent does not require an explicit model of the process dynamics and can operate in a model-free manner, which is a significant advantage in highly complex systems like FCC. DRL is particularly effective for the dynamic adjustment of key operational parameters such as reactor temperature, feed rate, and catalyst regeneration conditions in the regenerator. DRL, with its capacity for sequential decision-making in dynamic and complex environments,

offers novel solutions for dynamic optimization challenges in FCC. It enables the system to learn optimal strategies for controlling parameters like temperature, pressure, and feed rate through interaction and feedback. This approach shows high flexibility when facing sudden feedstock changes or equipment failures. Yield improvements resulting from DRL implementation in process optimization have reached up to 3%. Case studies have demonstrated that DRL can significantly enhance the yield of valuable products. For example, using DRL to automatically adjust reactor temperature and pressure can reduce process fluctuations and bring operation closer to the optimal operating point. This can lead to a 2% to 3% increase in gasoline yield and improved process stability. Furthermore, DRL can play a role in optimizing energy consumption and reducing the production of undesirable by-products, all of which contribute to the overall performance and environmental sustainability of the FCC unit. The key difference between ANN and DRL is that ANN is primarily used for static prediction and modelling, whereas DRL focuses on sequential decision-making and dynamic optimization in complex environments [22–25].

3.2 Enhancing Gasoline Yield and Quality with DRL

Another study demonstrated the effectiveness of DRL in the dynamic optimization of FCC gasoline yield and quality. In this scenario, a DRL agent continuously adjusted operational parameters such as riser temperature and catalyst feed rate to maximize gasoline yield while keeping octane quality within the desired range. The agent was trained through multiple simulations and trialanderror interactions within a virtual environment. Results showed an increase of up to 3% in gasoline yield while maintaining target octane quality. This emphasizes that DRL enables dynamic process optimization by learning complex decision-making strategies and can lead to more significant performance improvements than prediction only approaches [26].

3.3 Dynamic Optimization of Reactor Temperature and Pressure with DRL

In an advanced investigation, DRL was employed to achieve dynamic optimization of FCC reactor temperature and pressure to maximize overall unit performance under feedstock fluctuations and changing market conditions. The DRL agent was trained using an advanced simulation environment that included dynamic thermal and mass models of the FCC unit. The agent's objective was to find control policies that minimized temperature variations while increasing the yield of valuable products. Simulation results indicated that the DRL system reduced reactor temperature fluctuations by 20% and increased overall gasoline yield by 2%. This example underscores DRL's capability to manage dynamic processes and achieve higher operational stability [27].

3.4 Adaptive Control Combining ANN and DRL

Another study explored a hybrid approach that integrated ANN and DRL for advanced, adaptive control of the FCC unit. In this system, the ANN was used to create an accurate predictive model of the process dynamics, which then served as part of the environment for training the DRL agent. This combination allowed the DRL agent to respond rapidly to changes in operational conditions and adaptively adjust its control policies. The primary goal was to minimize the production of undesirable by-products (such as coke and dry gases). Results showed that using this combined approach reduced the production of undesirable by-products by up to 10% while preserving the yield of main products. This highlights the importance of combining the strengths of different AI techniques to solve more complex challenges in industrial settings [2].

4 Future Research

The application of AI in refineries, particularly FCC units, remains in its early stages, presenting substantial potential for future research.

4.1 Development of Hybrid and Composite Models

A significant research direction involves developing hybrid models that integrate data-driven approaches (such as AI) with models based on first principles (physical and chemical laws). These composite models can leverage the high accuracy of physics-based models and the flexibility of AI models, leading to more accurate and reliable modelling. Integrating AI with

dynamic process simulations can also help train DRL agents in more realistic environments.

4.2 Online and Adaptive Reinforcement Learning

Most DRL studies are conducted in simulated environments. Future research must focus on the implementation and testing of DRL in an **online and adaptive** manner within real FCC units. This involves developing algorithms capable of continuously learning from new data and adapting to changes in process dynamics without requiring a full retraining cycle.

4.3 Cybersecurity and AI Robustness

With increasing reliance on AI systems, issues concerning cybersecurity and the robustness of these systems against malicious attacks or systemic failures are becoming critically important. Future research should concentrate on developing strong security frameworks for industrial AI systems and finding solutions to detect and counteract unexpected or unsafe behaviors exhibited by AI models.

4.4 Value Chain Optimization with AI

Beyond optimizing a single FCC unit, AI can be utilized to optimize the entire refinery value chain, from production scheduling to inventory management and distribution. This requires integrating data from diverse sources and employing AI models for strategic and tactical decision-making on a broader scale.

5 Challenges and Limitations

Despite the significant potential of Artificial Intelligence in optimizing Fluid Catalytic Cracking (FCC) units, the implementation and operation of these intelligent systems are accompanied by several challenges and limitations that warrant careful consideration.

5.1 Data Quality and Quantity

The success of any AI system is highly dependent on access to high-quality and sufficient data. In refineries, process data may often be incomplete or contain significant measurement errors. Collecting, preprocessing, and validating vast amounts of historical process data present a major challenge. The lack of sufficient data for specific scenarios (such as emergency conditions or operation at suboptimal conditions) can negatively impact the generalizability of AI models.

5.2 Model Complexity and Interpret-ability

DL and DRL models, especially those with numerous hidden layers, can become highly complex, effectively acting as “black boxes.” This makes it difficult to understand precisely how the model arrives at a specific decision, which is a serious concern in safety-critical environments like refineries. Interpret-ability remains an active research area, but challenges still exist in providing clear and trustworthy explanations for complex AI decisions.

5.3 Need for Multidisciplinary Expertise

Successful implementation of AI systems in FCC requires a combination of expertise in Chemical Engineering, Control Engineering, Data Science, and Machine Learning. Finding a team with such diverse skills can be difficult. Furthermore, close collaboration between process engineers and AI specialists is essential for defining objectives, collecting data, and validating models.

5.4 Computational Costs and Infrastructure

Training DL and DRL models, especially for large and complex systems, demands high computational power, often involving the use of Graphics Processing Units (GPUs) or computing clusters. This can entail substantial initial capital expenditures for refineries. Moreover, the continuous maintenance and updating of the models and their associated infrastructure also require significant resources.

5.5 Portability and Generalizability

AI models trained on data from one specific FCC unit may not be easily portable or generalizable to other units with different designs, feed compositions, or operational conditions. This

necessitates retraining or, at minimum, fine-tuning the models for each specific unit, a process that is both time-consuming and costly.

6 Conclusion

The application of Artificial Intelligence, specifically Artificial Neural Networks (ANNs), Deep Learning (DL), and Deep Reinforcement Learning (DRL), has driven a revolution in the optimization and control of FCC units within refineries. These techniques offer unparalleled capabilities for accurately modelling complex processes, predicting operational parameters and product quality, and making optimal, real-time decisions. ANNs, with their inherent ability to accurately predict and model non-linear systems, play a crucial role in improving gasoline yield and controlling product quality. Deep Learning, as a step beyond ANNs, enables the modelling of more intricate phenomena, such as catalyst activity and process dynamics, with greater precision. Deep Reinforcement Learning, on the other hand, holds significant potential for enhancing overall yield and operational stability in FCC units due to its capability for sequential decision-making and dynamic optimization. Numerous case studies have demonstrated tangible improvements in product yields, reductions in energy and catalyst consumption, and enhancements in gasoline quality, all of which directly impact the profitability and operational sustainability of refineries. However, the implementation of these technologies is accompanied by inherent challenges, including data quality, model complexity and interpret-ability, the need for multidisciplinary expertise, computational costs, and model portability issues. Overcoming these hurdles requires investment in robust data infrastructure, the development of more interpretable algorithms, and the training of specialized human resources.

Conflict of Interest

No conflict of interest was declared by the authors.

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