



Multivariate Regression Approach in Modelling Catalytic Cracking Variables of Petroleum Refining

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Abstract: The ongoing digital transformation within the petroleum industry has accelerated the integration of data-driven methodologies for predictive analytics and process optimization. Despite these advances, conventional modelling techniques often struggle to capture the complex, nonlinear interdependencies that characterize refinery operations. This study proposes a statistical modelling framework for forecasting gasoline yield within the fluid catalytic cracking (FCC) unit of a commercial refinery, leveraging historical operational data spanning seven years. Key process variables including feed charge, regeneration temperature, riser temperature, gasoline temperature, and gasoline density were utilized to develop a multiple linear regression model. The resulting equation, demonstrates the quantitative relationship between gasoline yield (Y) and the selected predictors (X_1 to X_5). Model performance was evaluated using the coefficient of determination ($R^2 = 0.096$) and Pearson's correlation coefficient ($R = 0.290$), indicating a modest explanatory power and weak linear association. While the model's predictive strength is limited, it provides a transparent and interpretable baseline for assessing FCC performance and lays the groundwork for future integration of more advanced, nonlinear machine learning techniques. The findings affirm the relevance of statistical modelling as a practical tool in refinery environments where data quality and volume may constrain the application of complex algorithms.

Keywords: Fluid Catalytic Cracking, Gasoline yield, Multiple linear regression, Predictive modeling, Petroleum refining optimization

INTRODUCTION

Petroleum refining is a critical industrial process that transforms crude oil into marketable fuels and other petroleum products (Byrum *et al.*, 2021). The petroleum industry is one of the most rapidly developing industries and is projected to grow faster in the coming years (Lee *et al.*, 2021). The growing complexity of refining units, coupled with environmental constraints and market demands, has necessitated the integration of advanced process control, optimization, and data analytics techniques (Olaizola *et al.*, 2022). Among the fossil fuels, petroleum is more valuable to several businesses due to the production of extensive assortments of finished products (Adebiyi, 2022). Chemical separations involve often complex mixtures of molecules into individual components or mixtures of components with similar properties. Such separations are integral to a variety of technologies, such as the production of liquid fuels and chemicals for transportation as well as everything from plastic bags to sterile medical equipment (Brennecke & Freeman, 2020). In modern refining, the refining processes are classified as either physical separation or chemical conversion (Fahim *et al.*, 2009). Modern petroleum refining incorporates a wide variety of techniques for the physical separation and chemical conversion of crude petroleum components (Iulianelli & Drioli, 2020; Aljamali & Salih, 2021). Petroleum refining encompasses various unit operations that separate, convert, and treat crude oil into valuable end-products such as gasoline, diesel, jet fuel, kerosene, and lubricants (Robinson, 2024; Speight, 2024).

Core refining processes include atmospheric and vacuum distillation, catalytic cracking, hydrocracking, alkylation, reforming, and desulfurization (Nwaobi, 2021). Among these, Fluid Catalytic Cracking (FCC) plays a pivotal role in maximizing gasoline yield from heavy fractions of crude oil (Zhang *et al.*, 2021). According to (Khaldi *et al.*, 2023), FCC units rely on zeolite-based catalysts to break down large hydrocarbon molecules into lighter compounds under controlled temperature and pressure. The efficiency of this process hinges on multiple interrelated parameters such as riser temperature, pressure, catalyst circulation rate, and feed composition. Traditional methods of optimizing FCC operations often involve steady-state models and empirical adjustments based on operator experience (Selalame *et al.*, 2022; Zhu *et al.*, 2022). Refinery systems are inherently nonlinear, high-dimensional, and subject to dynamic disturbances (Rojas *et al.*, 2025). These characteristics make accurate modeling and real-time optimization complex. One of the most persistent challenges lies in managing the variability of crude oil feedstock [17]. Crude oil differs significantly in composition, sulfur content, and boiling point range, which affects the behavior of every downstream process. Refining strategies that work well for light, sweet crude (less than 0.5% weight sulfur content) may be ineffective or even problematic when processing heavier or sour crudes. This variability necessitates dynamic process adjustments and increases the complexity of refining operations, particularly in units such as the fluid catalytic cracking unit (FCCU), hydrocrackers, and atmospheric distillation towers (UJKA, 2021). Equipment reliability is another major concern. Refineries rely on an extensive network of pumps, compressors, reactors, heat exchangers, and columns that are prone to mechanical wear, corrosion, and fouling. Unexpected equipment failure can lead to operational downtime, safety hazards, and substantial financial losses (Douglas *et al.*, 2022; Pal *et al.*, 2023). While predictive maintenance and sensor-based monitoring have improved in recent years, integrating these systems across legacy infrastructure remains a challenge. Furthermore, refinery operations are characterized by multivariable, nonlinear process dynamics. Temperature, pressure, flow rates, and chemical composition must be continuously controlled within narrow operational windows (Ali *et al.*, 2021). These variables are often interdependent and respond unpredictably to fluctuations, making conventional control strategies such as PID loops insufficient in many cases. Achieving stability and optimal performance requires more advanced control systems and data-driven models that can adapt in real time.

Environmental regulations have also become increasingly stringent, placing additional pressure on refining operations (Dimitriadis *et al.*, 2021). Compliance with emission standards for sulfur, nitrogen oxides, and particulate matter requires costly process modifications and the integration of specialized units for flue gas treatment and wastewater management. These regulations not only increase operational expenses but also reduce flexibility in processing certain types of crude oil. Energy consumption is another critical issue in refining, given that it is one of the most energy-intensive industries globally (Tavella *et al.*, 2025). Efficient heat integration and energy recovery across different process units are essential for minimizing fuel costs and reducing the carbon footprint. However, fouling in heat exchangers, variability in operating conditions, and constraints in retrofitting older plants can undermine these efforts. Catalyst management further complicates refinery operations. Catalysts used in cracking, reforming, and hydro processing gradually lose activity due to coke formation, poisoning, or thermal stress (Jing *et al.*, 2020; Oyejide *et al.*, 2025). Ensuring effective regeneration without degrading performance is crucial, as catalyst activity directly influences conversion rates and product quality. Suboptimal catalyst behavior can lead to reduced yields and increased off-spec production. The explosion of process data from Distributed Control Systems (DCS), Programmable Logic Controllers (PLCs), and sensors offers opportunities for smarter decision-making, but it also presents challenges. Many refineries struggle with data integration, inconsistency in formats, and lack of standardized analytics platforms. As a result, much of the collected data remains underutilized, and decision-making still relies heavily on operator experience and historical trends rather than real-time analytics. Maintaining consistent product quality while optimizing yield is another delicate balancing act. Small variations in operating parameters can significantly affect product properties, requiring careful monitoring and adjustment. Yield optimization often depends on predictive models capable of handling complex interactions between variables. However, these models must be continually validated and recalibrated, which is time-consuming and computationally demanding. Statistical methods have long been employed in process industries to analyze variability, monitor quality, and improve performance (Md Nor *et al.*, 2020; Montgomery, 2020; Oyejide *et al.*, 2024). In petroleum refining, techniques such as regression analysis, design of experiments (DoE), statistical process control (SPC), and multivariate analysis are applied for understanding process behavior (Evangelista *et al.*, 2020). Regression models are used to quantify relationships between input and output variables, while multivariate statistical techniques like Principal Component Analysis (PCA) and Partial Least Squares (PLS) help in reducing data dimensionality and uncovering hidden patterns in large datasets. Qamar *et al.* (2024) emphasized the importance of detecting multicollinearity using the Variance Inflation Factor (VIF) to ensure model reliability and interpretability.

MATERIALS AND METHODS

This constitutes the plan guiding the process of data collection. It will highlight the methods and tools deployed in the pursuit of setting goals and objectives. Specifically, this chapter will show the research design, sources of data and data analysis techniques, validity, and reliability of research. Research design is the framework that specifies the type of information to be collected, the sources of data, and the collection procedure. It is the basic plan for data collection and analysis of the study. The primary objective involved obtaining data from the catalytic cracking of the refinery and carrying out analysis by way of developing a model for predicting future occurrences. This is applied research crafted to use past time series data. Fig. 1 is a chart showing the methodology structure.

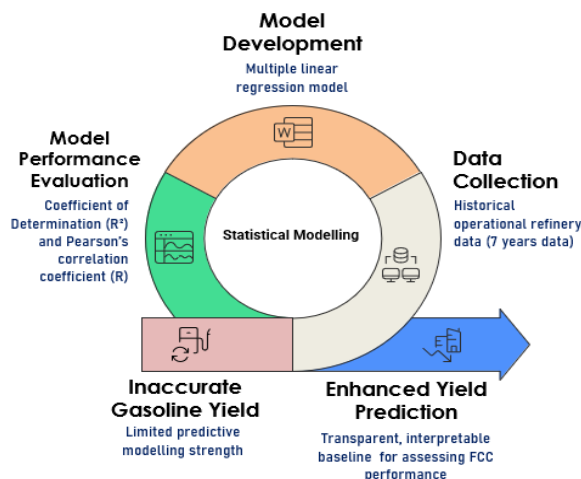


Fig. 1 Chart showing the statistical modeling framework for gasoline yield prediction in FCC unit using Multiple Linear Regression Model.

A. DATA COLLECTION

The data employed is obtained from the Warri Refining and Petrochemical Company, WRPC. Data for this study were collected from the refinery records, and they were sourced through personal contact with relevant authorities of the organization. The data were journalized in a notebook, but it is important to note that some entries were either missing or had no consistency in record maintenance, although the ones collected fell within 2013 and 2019. In data collection, emphasis was placed on the catalytic cracking section of the refinery. A 7-year secondary dataset was obtained from the archive of a commercial refinery. The observations were extracted as recorded.

B. METHOD OF DATA ANALYSIS

The responses on feed charge, regeneration temperature, etc., were used. The predictive model was developed based on these parameters. The multiple linear regression was used to develop a regression model to forecast the future occurrence of the variables relating to the catalytic cracking of the refinery.

Multiple Regression Model

The relationship between a set of independent variables and the response y is determined by a mathematical model called regression model. When there are more than two independent variables the regression model is called a multiple regression model.

The model is of the form

$$y = b_0 + b_1x_1 + \dots + b_nx_n$$

$$y = b_0 + b_1x_1 + b_2x_2 + \dots \quad (i)$$

(2 variable problem)

To solve equation (i), we need to develop a set of normal equation by multiplying the model by independent variable and SUM.

$$\Sigma y = \Sigma b_0 + b_1 \Sigma x_1 + b_2 \Sigma x_2 \quad (2)$$

$$\Sigma x_1 y = b_0 \Sigma x_1 + b_1 \Sigma x_1^2 + b_2 \Sigma x_1 x_2$$

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$$\Sigma x_2 y = b_0 \Sigma x_2 + b_1 \Sigma x_1 x_2 + b_2 \Sigma x_2^2 \quad (3)$$

Equations 1 to 3 are referred to as normal equations; and least square method was used to obtain the equation. Considering,

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \varepsilon \quad (4)$$

The method of the least squares was utilized to develop a set of normal equations as shown in Equation 4. Y is the dependent variable while x_1 to x_9 refers to the independent variables.

The key research instrument is the multivariate regression model in which the dependent variable (output) Y is the Gasoline Yield. The independent variables are the Feed charge, Regeneration temperature, Riser temperature, Gasoline Temp, and Gasoline density. These are represented by X_i , $i = 1, 2, \dots, n$.

The pristine equation was stated, and the set of normal equations was developed as shown in Equation 5;

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 \quad (5)$$

Coefficient of Determination

The coefficient of Determination is used to validate the developed model.

r^2 Coefficient of determination is the measure r,

$$r^2 = \left[\frac{n \Sigma xy - \Sigma x \Sigma y}{\sqrt{[n \Sigma x^2 - (\Sigma x)^2][n \Sigma y^2 - (\Sigma y)^2]}} \right]^2 \quad (6)$$

r^2 (as obtained with Equation 6) is used when we want to know the degree to which the observed value variability is accounted for. The coefficient of Determination measures the extent to which the independent variable x can account for the perceived variability in the value of the dependent variable y .

RESULTS AND DISCUSSION

The current section shows the results of the data analysis, and their corresponding discussion.

Table-1 Presentation of the variables for the regression model

Feed Charge	Regeneration Temp	Riser Temp	Gasl Temp	Gasl Density	Reactor Pressure	Catalyst/ Oil Ratio	Coke Yield	Steam Flow	Gasl Yield
KL/hr	°C	°C	°C	Kg/cm ²	bar		wt%	Kg/hr	m ³ /hr
X1	X2	X3	X4	X5	X6	X7	X8	X9	Y
7040.3	40890.5	30170.5	2307.8	44.976	18.25	7.32	12.44	25.80	3285.74
119.3271	693.059	511.3644	39.11525	0.762	1.10	0.42	0.88	1.93	55.69

Considering Equation (5),

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9$$

The method of the least squares was utilized to develop a set of normal equations. Y is the dependent variable, while x_1 to x_9 refer to the independent variables.

The variables of equations (7) to (16) can now be obtained by converting the equations into their matrix form.

$$17943 = 11\beta_0 + 425\beta_1 + 2777\beta_2 + 1177\beta_3 + 1300\beta_4 + 1178\beta_5 + 1833\beta_6 + 2419\beta_7 + 2343\beta_8 + 449\beta_9 \quad (7)$$

$$678956 = 425\beta_0 + 17567\beta_1 + 95678\beta_2 + 38422\beta_3 + 44140\beta_4 + 36631\beta_5 + 63407\beta_6 + 83343\beta_7 + 79474\beta_8 + 150861\beta_9 \quad (8)$$

$$4479827 = 2777\beta_0 + 95678\beta_1 + 720103\beta_2 + 256849\beta_3 + 293682\beta_4 + 246516\beta_5 + 408368\beta_6 + 545918\beta_7 + 529612\beta_8 + 1020536\beta_9 \quad (9)$$

$$1973011 = 1177 \beta_0 + 38422 \beta_1 + 256849 \beta_2 + 135621 \beta_3 + 134546 \beta_4 + 117795 \beta_5 + 175822 \beta_6 + 242244 \beta_7 + 243152 \beta_8 + 493227 \beta_9 \quad (10)$$

$$2156433 = 1300 \beta_0 + 44140 \beta_1 + 293682 \beta_2 + 134546 \beta_3 + 159060 \beta_4 + 129288 \beta_5 + 194122 \beta_6 + 269515 \beta_7 + 266862 \beta_8 + 543954 \beta_9 \quad (11)$$

$$1959927 = 1178 \beta_0 + 36631 \beta_1 + 246516 \beta_2 + 117795 \beta_3 + 129288 \beta_4 + 135828 \beta_5 + 169103 \beta_6 + 229443 \beta_7 + 229729 \beta_8 + 471701 \beta_9 \quad (12)$$

$$2985980 = 1833 \beta_0 + 12720 \beta_1 + 408368 \beta_2 + 175822 \beta_3 + 194122 \beta_4 + 169103 \beta_5 + 328469 \beta_6 + 361866 \beta_7 + 354470 \beta_8 + 677153 \beta_9 \quad (13)$$

$$3971779 = 2419 \beta_0 + 83343 \beta_1 + 545918 \beta_2 + 242244 \beta_3 + 269515 \beta_4 + 229443 \beta_5 + 361866 \beta_6 + 537213 \beta_7 + 486608 \beta_8 + 959240 \beta_9 \quad (14)$$

$$3892693 = 2343 \beta_0 + 79474 \beta_1 + 529612 \beta_2 + 243152 \beta_3 + 266862 \beta_4 + 229729 \beta_5 + 354470 \beta_6 + 486608 \beta_7 + 515581 \beta_8 + 961280 \beta_9 \quad (15)$$

$$7554071 = 4491 \beta_0 + 150861 \beta_1 + 1020536 \beta_2 + 493227 \beta_3 + 543954 \beta_4 + 471701 \beta_5 + 677153 \beta_6 + 959240 \beta_7 + 961280 \beta_8 + 2033679 \beta_9 \quad (16)$$

Solving the set of normal equations, we have:

$$\beta_0 = 1548.4839$$

$$\beta_1 = -1.5224$$

$$\beta_2 = -0.2039$$

$$\beta_3 = 1.1179$$

$$\beta_4 = 0.0380$$

$$\beta_5 = 0.3411$$

$$\beta_6 = -1.2637$$

$$\beta_7 = -0.0433$$

$$\beta_8 = 0.5581$$

$$\beta_9 = 0.3272$$

$$\therefore y = 1548.4839 - 1.5224X_1 - 0.2039X_2 + 1.1179X_3 + 0.0380X_4 + 0.3411X_5 - 1.2637X_6 - 0.0433X_7 + 0.5581X_8 + 0.3272X_9$$

CONCLUSION

The modeling of catalytic cracking has been successfully carried out. The result showed that the multiple linear regression model provided average reliability and accuracy, having a correlation coefficient R of 0.95084 and the coefficient of determination R² as 0.723079.

- (i) Multiple linear regression was found to be reliable for predicting the gasoline yield
- (ii) A model to predict gasoline yield from refining parameters has been developed.

The multivariate linear regression model is found suitable and applied to the problem examined in this study. The study has provided reasonable information to the existing literature on the application of a regression model for a refinery operation. The significance of the research lies in its potential to enhance refinery operations through improved prediction models, providing decision-making support, optimizing resource use, and reducing costs. It offers value to industry stakeholders, policymakers, environmental initiatives, and the academic community. The proposed framework bridges data-driven approaches with domain expertise, contributing to scalable and validated modelling strategies.

RECOMMENDATIONS

Considering the outcome of the results obtained from the study regarding Agbor and its environs, the following practices/activities are recommended.

- i. Long-Term Monitoring of vegetative patterns/trends and adaptive management of vegetative cover to reduce erosivity of rainfall and enhance runoff interception thereby reducing the generation of sediments and sediment flow, and
- ii. Provision of easy access to climatic/climatological data to enable future studies on the existing trends of erosion in the long run with regards to rainfall specifically

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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