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Proposed Improvement of Diesel and Jet Fuel Planning Management at PT. OGC Using Six Sigma DMAIC

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ABSTRACT

PT. OGC faces inaccuracies in diesel and jet fuel forecasting, leading to inventory shortages, higher logistics costs, and potential public dissatisfaction, which also impacts Indonesia's energy self-sufficiency and oil-gas trade deficit. This research proposes improvements to diesel and jet fuel planning management at PT. OGC using the Six Sigma DMAIC methodology to identify root causes of inventory issues and enhance planning accuracy. A mixed-methods approach was employed, combining primary and secondary data with SIPOC analysis, forecast error measurements (MAD, MAPE, DPMO, sigma level), correlation analysis, fishbone diagrams, Pareto charts, and process capability indices (Cp, Cpk). Simulations validated the proposed solutions. Current forecasting accuracy is below acceptable levels: diesel MAPE at 5.89% (exceeding the 5% SLA tolerance) and jet fuel MAPE at 11.26%. Cp and Cpk remained below 1.0. Root causes included weak forecasting methods, misaligned turnaround schedules with demand, and emergency shutdowns. Improvement initiatives reduced forecast errors: the ARIMA–XGBoost hybrid model lowered diesel MAPE to 4.21%, and the SARIMA–LSTM hybrid model reduced jet fuel MAPE to 4.00%. The proposed improvements effectively reduce forecasting errors, increase production stability, and decrease stock problems. Recommendations include adopting hybrid AI/ML forecasting models, aligning turnaround schedules, digitizing preventive maintenance, and implementing a monitoring dashboard with regular audits.

INTRODUCTION

As a state-owned company, PT. OGC (Oil & Gas Company) is responsible for maintaining the security of the national energy supply, including diesel and jet fuel. These fuels come from the same fraction of crude oil that is needed for the transportation and industrial sectors (Sharma & Ghoshal, 2015). In the 2021-2024 period, total imports of diesel and jet fuel reached USD 5.30 billion. This contributed to a deepening of the oil and gas trade deficit, which had an impact on national economic resilience.

Table 1 Import Value of Diesel and Jet Fuel

Period	Import Value (Billion USD)		
	Jet Fuel	Diesel	Total
2021	0.12	-	0.12
2022	1.09	0.35	1.43
2023	0.50	0.10	0.60

2024	2.06	1.09	3.15
Total	**3.76**	**1.54**	**5.30**

Source: PT. OGC Internal Data (2021–2024)

PT. OGC strives to improve energy security for diesel and jet fuel. The main issue faced is how to maintain the supply-demand balance and inventory management of both products. To optimize inventory costs, PT. OGC strives to maintain stock levels within specified safe limits. However, during certain periods, there is an imbalance between supply and demand, which risks causing understock during peak season and excess stock afterwards. This condition not only disrupts distribution operations but also has an impact on logistics costs, production efficiency, and affects the company's Cost of Goods Sold.

Table 2 Inventory Impact Diesel & Jet Fuel on COGS

Period	Inventory Impact on COGS (billion USD)
2021	762.1
2022	917.22
2023	275.42
2024	151.59

Source: PT. OGC Internal Data (2021–2024)

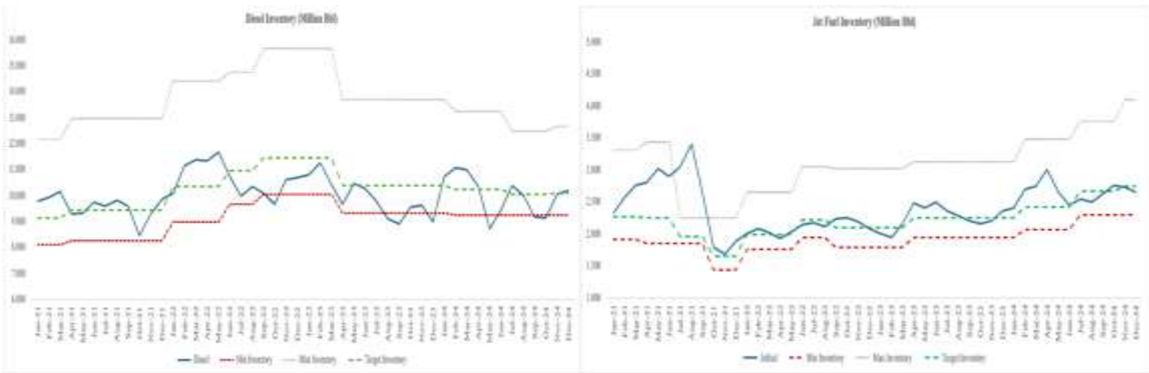

Figure 1. Inventory Diesel & Jet Fuel

Source: PT. OGC Internal Data (2021–2024)

Forecasting is an important aspect of operational and strategic decision-making in the supply chain, especially for demand management, capacity planning, and inventory management (Petropoulos et al., 2022). This study uses time series analysis because this method is most commonly used in supply chain planning, including moving average and exponential smoothing. This model predicts the future based on historical data, such as previous period sales data (Jacobs & Chase, 2024). Another widely used method is ARIMA (Autoregressive Integrated Moving Average), which combines autoregressive (AR) and moving average (MA) models based on the Box–Jenkins methodology (Box et al., 2015). ARIMA can handle both stationary and non-stationary data through the differencing process of autocorrelation between lags (Qin et al., 2019). For seasonal data, SARIMA (Seasonal ARIMA) is used with additional seasonal parameters (Smith & Johnson, 2020). The accuracy of ARIMA depends on the length of the time series that fully reflects the trend pattern (Qin et al., 2019). In the context of operations and supply chains, exponential smoothing and ARIMA are one of the main methods because they are adaptive to trends and seasonal patterns (Petropoulos et al., 2022).

Conventional methods currently have limitations in capturing non-linear patterns and dynamic changes (Petropoulos et al., 2022). AI/ML approaches are used to improve the accuracy and adaptability of forecasts because they can learn complex and non-linear relationships without strict stationarity assumptions (Douaioui et al., 2024). LSTM is effective for non-stationary and fluctuating data and is more accurate than ARIMA in capturing short- and long-term patterns (Maleki et al., 2024). XGBoost excels at predicting non-linear patterns with high efficiency and performs well in energy demand forecasting (Krause et al., 2024). Prophet uses an additive approach with trend, seasonal, and special event components, and is easy to interpret (Petropoulos et al., 2022; (Taylor & Letham, 2018). Hybrid models such as ARIMA–LSTM, SARIMA–LSTM, and ARIMA–XGBoost combine the strengths of statistics and ML and can improve accuracy by 20–30% compared to single models (Krause et al., 2024; (Maleki et al., 2024).

Forecast error is the difference between actual demand and forecast results, because demand is influenced by various complex factors that are difficult to model (Jacobs & Chase, 2024). To assess the accuracy of forecasts, statistical measures such as Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Mean Absolute Percentage Error (MAPE) are used (Maleki et al., 2024). Tracking Signal (TS) is used to detect forecasting bias by measuring whether the forecast results consistently follow upward or downward trends in demand (Jacobs & Chase, 2024).

Forecast Value Added (FVA) is used to assess the extent to which adjustments to forecast results can improve accuracy and reduce bias. Adjustments are only effective for about half of SKUs; positive adjustments often reduce accuracy, while negative adjustments generally improve it (Fildes et al., 2025). The FVA value is calculated using the formula

$$\text{FVA} = \frac{\text{Adjusted Method Error}}{\text{Baseline Method Error}}$$

If FVA < 1, accuracy increases; FVA > 1, accuracy decreases; and FVA = 1, there is no change. FVA is important for assessing model reliability and the added value of forecasting in business decision-making (Petropoulos et al., 2022).

Process Capability Ratio (Cp) and Process Capability Index (Cpk) are used to assess the ability of a process to meet specification limits. Cp measures the level of process capability; a process is considered capable if Cp ≥ 1.0, with an industry standard of Cp = 1.33 (4-sigma) which is equivalent to approximately 64 defects per million units (Heizer et al., 2020). Cp, is computed as:

$$C_p = \frac{\text{Upper specification} - \text{Lower specification}}{6\sigma}$$

Cpk indicates how centered the process is on the specification limits; Cpk = 1.0 means variation within ±3 sigma (±2,700 defects per million), while Cpk = 2.0 indicates a highly reliable process with less than 3.4 defects per million (Heizer et al., 2020). Cpk, is computed as:

$$C_{pk} = \text{Minimum of}\left[\frac{\text{Upper specification limit} - \bar{X}}{3\sigma}, \frac{\bar{X} - \text{Lower specification limit}}{3\sigma}\right]$$

Inventory management aims to maintain a balance between supply and demand to avoid shortages or excess stock and to increase efficiency and profitability (Heizer et al., 2020). Key challenges in Indonesia's downstream supply chain include demand uncertainty, dependence on maritime transportation, diverse geographic conditions, and the risk of distribution disruptions (Raymutia & Soemardi, 2024). Inventory decision-making involves a trade-off between holding costs and service levels; high inventory increases reliability but increases costs, while low inventory reduces costs but risks stockouts (Tan et al., 2024). To maintain operational continuity, supply chain resilience is necessary—namely, the ability to recover from disruptions through visibility, flexibility, redundancy, and collaboration (Hart Nibbrig et al., 2025; Juan et al., 2021). Strategies such as stockpiling, multi-sourcing, and flexible supply contracts help increase resilience to demand fluctuations and supply disruptions (Guo et al., 2025).

Six Sigma is a comprehensive system that serves as a strategy, discipline, and set of tools to improve the quality and efficiency of business processes by reducing defects, lowering costs, and increasing customer satisfaction (Heizer et al., 2020). This approach describes processes with a very high level of accuracy (99.9997%) and is measured using the Defects per Million Opportunities (DPMO) metric (Jacobs & Chase, 2024). Six Sigma is a set of techniques and tools for process improvement that has proven effective in reducing costs and increasing operational efficiency, including fleet availability and reducing supply chain lead times (Maryadi & Ichtiarto, 2021; Stanivuk et al., 2020). However, its implementation often faces obstacles such as lack of management support, investment, training, and employee resistance (Ali et al., 2020; Papic et al., 2017). The core Six Sigma methodology is executed through the DMAIC (Define, Measure, Analyze, Improve, Control) cycle, which focuses on understanding customer needs and continuous process improvement (Jacobs & Chase, 2024). The Define phase identifies problems and Critical to Quality (CTQ) characteristics, the Measure phase assesses process performance, the Analyze phase identifies the root cause of the problem, the Improve phase establishes solutions to eliminate the causes of defects, and finally, the Control phase ensures the sustainability of improvements. As technology advances, the DMAIC 4.0 concept now integrates big data analytics, IoT sensors, data mining, and deep learning to improve the effectiveness of real-time monitoring and decision-making (Pongboonchai-Empl et al., 2025).

Based on the background and problems described above, this study aims to: (1) identify the main root causes of inaccuracies in diesel and jet fuel demand forecasting and production planning at PT. OGC; (2) propose and validate improvement strategies using the Six Sigma DMAIC approach, including the application of hybrid forecasting models (ARIMA–XGBoost and SARIMA–LSTM); and (3) design a sustainable control framework through KPIs, dashboards, SOP updates, and regular audits to maintain long-term planning accuracy. The benefits of this research are twofold. Theoretically, this study contributes to the literature on supply chain management and operations research by demonstrating the integration of Six Sigma DMAIC with hybrid AI/ML forecasting models (ARIMA–XGBoost and SARIMA–

LSTM) in the context of energy inventory planning, an area that has received limited empirical attention. The findings also extend the application of process capability analysis (Cp, Cpk) and Forecast Value Added (FVA) to petroleum product supply chains. Practically, the results provide PT. OGC and other state-owned energy companies with actionable recommendations to reduce forecast errors, align refinery turnaround schedules with seasonal demand, implement digital preventive maintenance, and improve inventory cost efficiency, ultimately supporting Indonesia's national energy security objectives.

METHOD

This research is based on two main research questions (RQs). RQ1 aims to identify the main factors causing inaccuracies in fuel demand and stock level planning through a mixed methods approach, combining a literature review, qualitative and quantitative analysis, document analysis, historical data, and focus group discussions (FGDs). Analytical tools such as SIPOC diagrams, statistical analysis, fishbone diagrams, and Pareto diagrams were used to identify root causes. RQ2 focuses on formulating effective improvement strategies through a literature review, mixed methods analysis, and data from discussions and document analysis. This research also includes thematic analysis, stakeholder mapping, and a review of standard operating procedures (SOPs), resulting in recommendations for practical solutions and implementation plans.

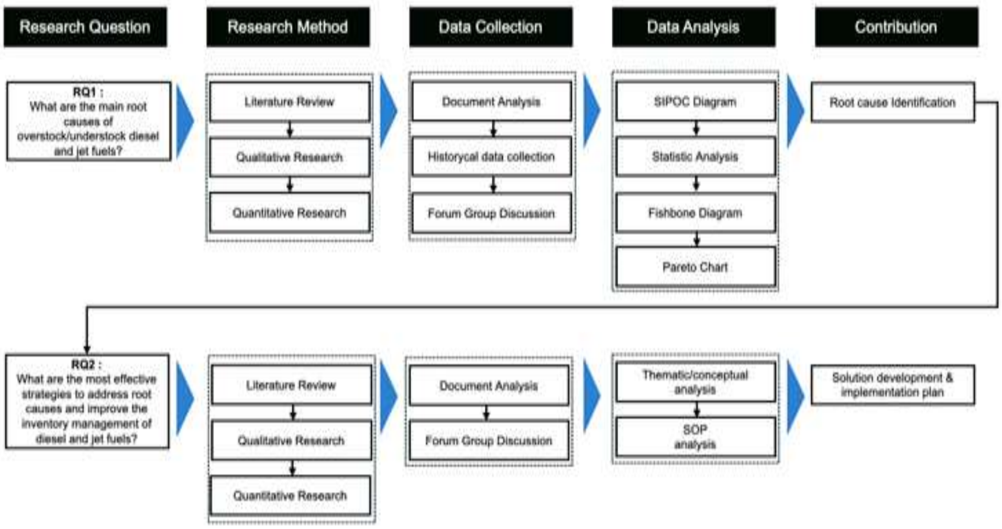

Figure 2. Research Methodology
Source: Author's elaboration (2025)

This research uses primary and secondary data to ensure comprehensive analysis. Primary data was obtained through the stages of objective determination, participant selection, FGD implementation, result validation, and data processing. Meanwhile, secondary data was collected from company reports, journals, books, standard operating procedures, government regulations, company policies, and other official publications. The analysis focuses on the period 2021–2024 to represent post-pandemic conditions. Each stage in the DMAIC (Define, Measure, Analyze, Improve, Control) framework is implemented with specific analytical tools and methods to define problems, measure performance, identify root causes, propose improvements, and establish control mechanisms to ensure continuous improvement.

Table 3 Detail Analysis Method

Phase	Analysis Method	Activity
Define	Project Charter, SIPOC Diagram, Literature Review	Observation, Focus Group Discussion, Literature Review
Measure	Forecast Error Analysis (MAD, MAPE, DPMO, Tracking Signal, Cp, Cpk, FVA), Correlation Analysis	Historical Data Retrieval and Analysis
Analyze	Fishbone Diagram, Pareto Chart	Data Analysis, Focus Group Discussion
Improve	Simulation, Scenario Evaluation	Scenario Testing, Evaluation
Control	Statistical Control Charts, Dashboard Monitoring	Review and Implementation of Corrective Actions

Source: Compiled by author based on Six Sigma DMAIC framework (2025)

RESULT AND DISCUSSION

1. Define Phase

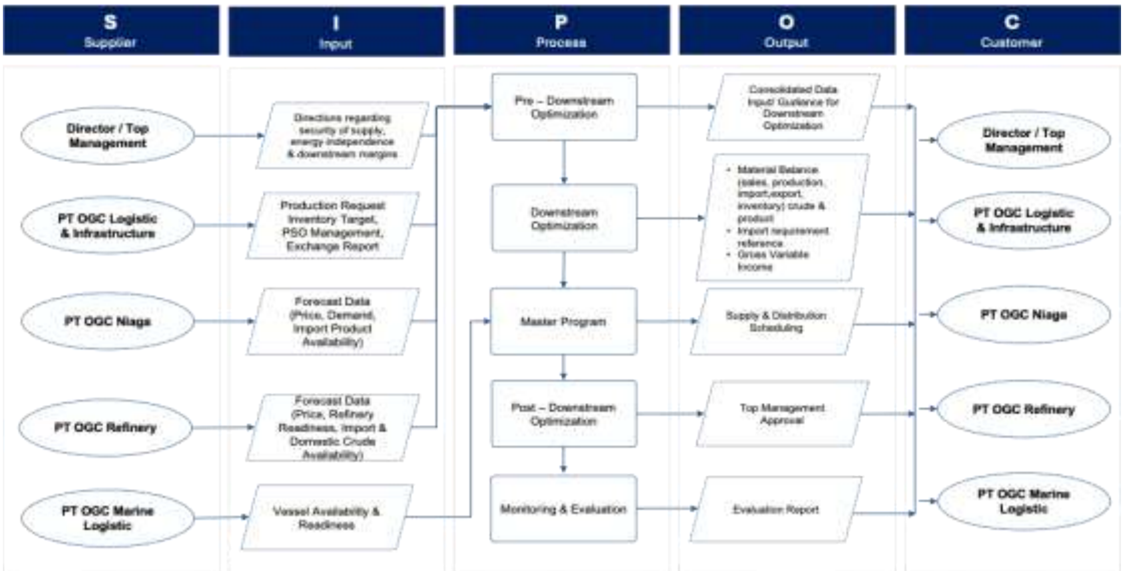

Figure 3. SIPOC Diagram Existing Process

Source: Author's elaboration based on PT. OGC process mapping (2025)

In the Define Phase, the research identified key issues in diesel and aviation fuel demand and production planning that led to stock imbalances. Using the SIPOC Diagram, PT.OGC's Downstream Optimization process was mapped as an integrated flow that aligns the supply and demand of crude oil and refined products across all sub-holdings. The goal is to ensure that national energy needs are met, supply security is maintained, and margin optimization is achieved. This process takes place over a four-month cycle (M+1 -M+4). Data is obtained from various functions, including PT.OGC Logistics & Infrastructure, PT OGC Niaga, PT OGC Refinery, and PT OGC Marine Logistic. The final result is a material balance that includes production plans, imports/exports, inventory, and margins, which is used as a basis for strategic and operational decision-making.

The Demand Forecast process is conducted by PT OGC Niaga to estimate diesel and aviation fuel demand based on historical data, market trends, and economic indicators, which serve as a reference for the PT.OGC Logistics & Infrastructure in setting production and stock targets. Furthermore, PT OGC Refinery's Production Planning utilizes Linear Programming (LP) to maximize efficiency and margins. The main outputs include refinery production plans, crude allocations, raw material requirements, and Gross Variable Income (GVI), which form the basis for PT. OGC Group's integrated planning.

2. Measure Phase

The Measure Phase aims to determine the appropriate measurement method and objectively assess process performance. Statistical analysis is performed to calculate forecast error using MAD, MAPE, MSE, and bias indicators, and to assess process capability using DPMO and Sigma Level with a maximum error limit of 5% as per PT. OGC's Service Level Agreement (SLA). Cp and Cpk values are used to measure process consistency against targets, while Forecast Value Added (FVA) assesses the increase in accuracy between planning M+3 and M+1. The analysis uses historical monthly data for the 2021–2024 period for diesel and aviation fuel demand and production plans.

	Diesel Demand Forecast			Jet Fuel Demand Forecast		
	M+3	M+2	M+1	M+3	M+2	M+1
Mean Squared Error (MSE)	1,109,214	1,191,932	1,207,203	78,613	75,846	53,941
Mean Absolute Deviation (MAD)	852	909	900	219	217	180
Mean Average Percentage Error (MAPE)	5.59	5.94	5.89	14.65	14.57	11.26
Defects Per Million Opportunities (DPMO)	416,666.67	520,833.33	500,000.00	750,000.00	729,166.67	687,500.00
Sigma Level	1.71	1.45	1.5	0.83	0.89	1.01
Process Capability (Cp)	0.2	0.21	0.2	0.04	0.04	0.06
Process Capability Index (Cpk)	-0.05	-0.08	-0.07	-0.17	-0.16	-0.14
Forecast Value Added (FVA)		-6.26%	0.93%		0.59%	22.69%

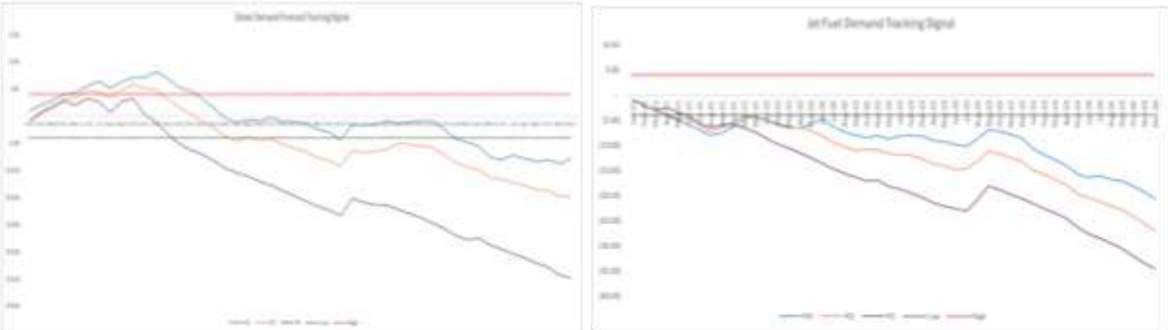

Figure 4. Existing Demand Forecast Performance

Source: PT. OGC Internal Data (2021–2024); processed by author

The analysis results show that accuracy increases as the implementation date approaches. In the diesel demand forecast, M+3 has the lowest error (MAPE 5.59%), but all periods show negative Cpk, indicating the process is not yet stable. The FVA value is positive only at M+1 (0.93%), indicating a slight increase in accuracy. Meanwhile, for aviation fuel forecasting, M+1 demonstrated the best performance with a MAPE of 11.26% and the highest FVA of 22.69%, despite still having low process capability. Tracking signal analysis revealed a strong negative bias, particularly for diesel fuel (MRF) M+1, indicating a tendency to under-forecast.

	Diesel Production Planning			Jet Fuel Production Planning		
	M+3	M+2	M+1	M+3	M+2	M+1
Mean Squared Error (MSE)	1,072,250	611,930	165,296	129,806	89,400	27,534
Mean Absolute Deviation (MAD)	745	557	292	290	219	123
Mean Average Percentage Error (MAPE)	7.61	5.48	2.88	19.46	14.94	8.27
Defects Per Million Opportunities (DPMO)	479,166.67	354,166.67	104,166.67	812,500.00	625,000.00	458,333.33
Sigma Level	1.55	1.87	2.76	0.61	1.18	1.6
Process Capability (Cp)	0.1	0.15	0.28	0.04	0.05	0.09
Process Capability Index (Cpk)	-0.11	-0.03	0.23	-0.26	-0.2	-0.12
Forecast Value Added (FVA)		28.04%	47.49%		23.23%	44.58%

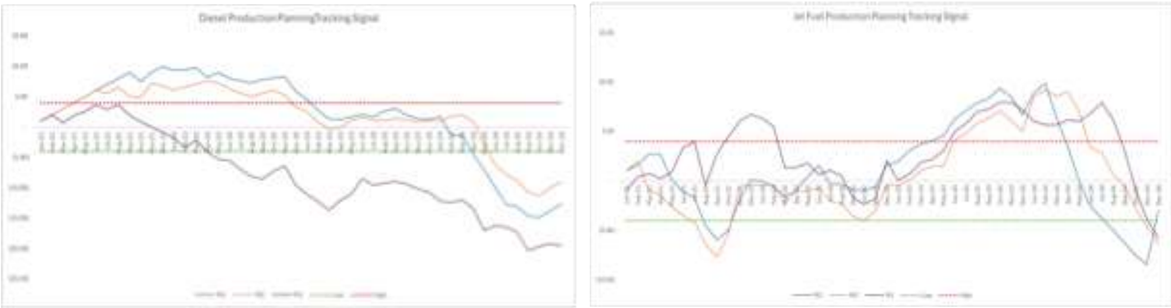

Figure 5. Existing Production Planning Performance

Source: PT. OGC Internal Data (2021–2024); processed by author

For production planning, performance improved significantly in M+1, with the lowest error (MRF for diesel fuel 2.88%; aviation fuel 8.27%) and the highest FVA (47.49% for diesel fuel and 44.58% for aviation fuel). Sigma Level and Cpk values also increased, indicating improved process control, although not yet fully stable. Tracking signal patterns showed that diesel fuel planning was more accurate and consistent than aviation fuel, which remained volatile and prone to bias. Overall, the results of the Measure phase confirmed that the closer the planning period is to the actual production date, the higher the forecast accuracy and added value.

3. Analyze Phase

The Analysis Phase aims to identify the root causes of inaccurate diesel and aviation fuel demand and production planning. Analysis using a 5M+1E (Man, Method, Machine, Material, Measurement, Environment) fishbone diagram indicates that the primary causes stem from method and measurement factors.

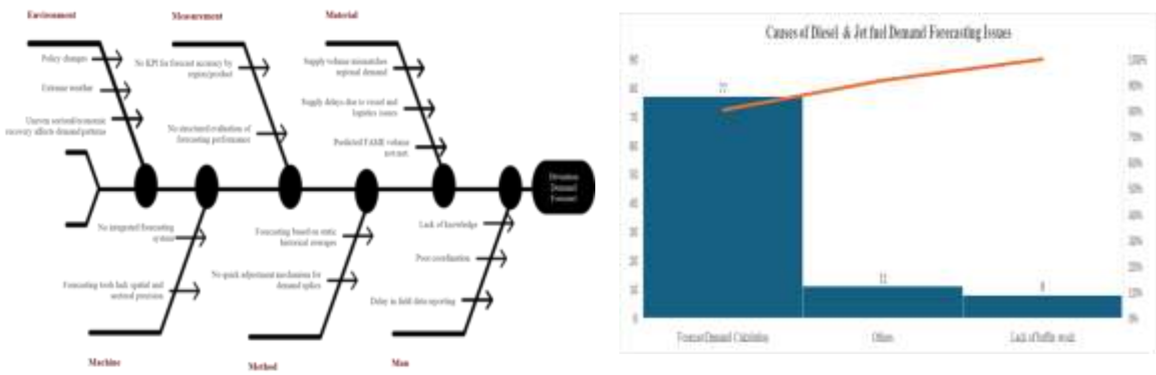

Figure 6. Fishbone Diagram of Root Causes for Demand Forecasting Inaccuracies

Source: Author's analysis based on FGD and PT. OGC data (2025)

Forecasting methods are still based on historical data without adjustments for seasonal patterns and changes in actual demand, while the evaluation system lacks specific KPIs for each region. Other factors include reporting delays, lack of integration of analytical tools, mismatched supply volumes, and environmental influences such as government policies and extreme weather (Zhu, 2023). Pareto analysis results indicate that forecasting methods that do not reflect actual consumption patterns are the dominant cause.

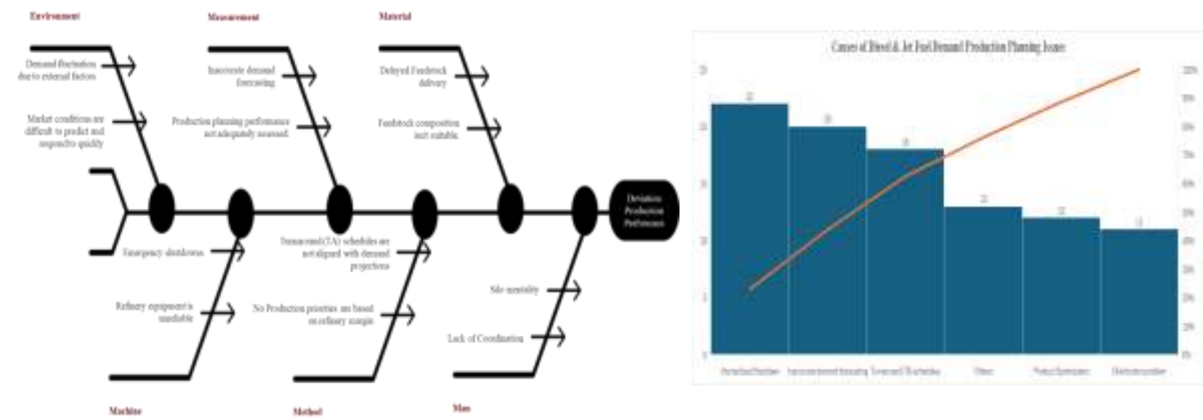

Figure 7. Pareto Chart of Root Causes for Production Planning Deviations

Source: Author's analysis based on PT. OGC internal data and FGD (2025)

In production planning, the main causes include refinery turnaround (TA) schedules that are not aligned with peak demand, unplanned shutdowns, and forecast inaccuracies. Furthermore, supply delays, differences in feedstock composition, and margin-based production priorities exacerbate the imbalance between production and market demand. These factors account for more than 90% of the deviations. Therefore, the focus of improvements is directed at increasing refinery reliability, synchronizing TA schedules, and refining forecasting measurement methods and systems to make planning more accurate and adaptive.

4. Improvement Phase

In the Improvement Phase, solutions were designed to address the root causes of the diesel and aviation fuel (aviation fuel) demand and production planning issues identified in the analysis phase. Trials were conducted comparing existing forecasting methods with new, historical data-based methods to assess the impact of implementing the new system and identify solutions for accuracy improvements.

Table 4 Diesel & Jet Fuel Forecast Demand Method Comparison

Method	Forecast Method	Diesel Forecast MSE	Diesel Forecast MAD	Diesel Forecast MAPE	Diesel Forecast % Improvement MAPE on Existing	Jet Fuel Forecast MSE	Jet Fuel Forecast MAD	Jet Fuel Forecast MAPE	Jet Fuel Forecast % Improvement MAPE on Existing
	Existing	*1,207,203.23*	*900.15*	*5.89*	-	*53,940.93*	*179.80*	*11.26*	-
Conventional	SMA 2	1,544,596.00	951.33	6.09	-3%	37,759.81	160.13	10.18	10%
	SMA 3	1,414,903.00	915.75	5.82	1%	44,804.71	176.16	10.69	5%
	SMA 4	1,532,479.00	948.62	6.02	-2%	52,849.15	197.09	11.74	-4%
	WMA 2	1,455,577.00	975.39	6.26	-6%	35,019.82	149.40	9.39	17%
	WMA 3	1,387,593.00	892.04	5.70	3%	34,861.72	146.79	9.12	19%
	WMA 4	1,421,660.00	899.96	5.73	3%	35,623.46	150.51	9.34	17%
	Single ES	1,388,029.16	918.17	5.86	1%	35,399.68	145.77	9.26	18%
	Double ES	1,456,516.84	930.44	6.04	-3%	36,532.28	150.01	9.54	15%
	ARIMA	1,649,543.81	1,006.41	6.48	-10%	36,151.15	148.68	9.45	16%
	SARIMA	7,866,537.15	1,373.86	9.15	-55%	32,821.34	146.00	9.35	17%
AI/ML	LSTM	1,082,047.00	794.16	4.74	20%	24,164.54	126.78	5.15	54%
	XGBOOST	1,353,992.66	912.92	5.51	6%	17,320.66	119.11	5.07	55%
	Prophet	921,803.03	761.83	4.89	17%	247,152.80	476.25	20.86	-85%
Hybrid	ARIMA LSTM	1,694,227.18	1,028.23	5.99	-2%	42,758.18	189.49	8.01	29%
	SARIMA LSTM	1,552,876.27	727.01	4.56	23%	**15,513.85**	**100.68**	**4.00**	**64%**
	ARIMA XGBOOST	**863,379.10**	**727.57**	**4.21**	**29%**	53,198.37	210.15	8.69	23%

Source: Simulation results based on PT. OGC historical data (2021–2024)

For demand forecasting, there is currently no standard method; calculations are based on business unit input without statistical validation. Analysis of various methods showed that ARIMA–XGBoost Hybrid provided the best results with a MAPE of 4.21%, more accurate than both conventional and AI/ML methods. Meanwhile, for aviation fuel demand, the best method was SARIMA–LSTM Hybrid with a MAPE of 4.00%, a MAD of 100.68, and an MSE of 15,513.85. This hybrid AI/ML method is superior because it is able to capture non-linear patterns and volatility in energy data (Petropoulos et al., 2022). Improvements to the demand planning process include the addition of a Challenge Session and benchmarking against the hybrid AI/ML method to validate projections from each business unit. Adopting artificial intelligence (AI) and machine learning–based optimization models that analyze historical data and external factors in real time to address supply chain complexity is recommended (Liang et al., 2025). This process improves transparency, cross-functional collaboration, and statistical accountability in planning (Aldabbagh et al., 2024; Barman, 2025) . Furthermore, SLAs and KPIs need to be expanded to measure accuracy from M+3 to M+1, with gradual targets for diesel and aviation fuel.

For production planning, improvements are focused on three main aspects: Increasing production accuracy targets from M+3 to M+1 with the same standards as forecast demand. Aligning refinery turnaround (TA) schedules with seasonal demand patterns to increase flexibility and reduce the risk of production shortfalls (Hart Nibbrig et al., 2025). Implementing AI- and IoT-based digital preventive maintenance to predict potential refinery equipment disruptions and reduce downtime by up to 90% (Rakholia et al., 2025). These improvements are expected to improve forecast accuracy, operational reliability, and the resilience of PT. OGC's energy supply chain.

5. Control Phase

The Control Phase ensures that the improvements from the Improvement phase are sustainable and integrated into the company's operations. This phase maintains processes within statistical control limits (Heizer et al., 2020), and also emphasizes the importance of audit systems, data-driven monitoring, and a robust organizational structure (Jacobs & Chase, 2024). The primary focus is on maintaining demand forecast accuracy and refinery production reliability. Control charts are used to monitor process stability through signal tracking. If values exceed the control limits (±4), a review of the forecasting method is required (Heizer et al., 2020). KPIs and SLAs are adjusted to measure accuracy across the M+3 to M+1 period, with daily monitoring and monthly evaluations. The Monitoring Dashboard displays key indicators such as MSE, MAD, MAPE, planned-to-actual production comparisons, and inventory, to ensure model accuracy and regular updates (Qin et al., 2019). All improvements are documented in new SOPs and audited periodically to ensure consistency and effectiveness of implementation.

CONCLUSION

The following conclusions were obtained based on the analysis using the Six Sigma DMAIC approach: 1) The main root causes of the imbalance in diesel and aviation fuel stocks are weak forecasting methods that are still historically based and unable to capture seasonal patterns. 2) Production planning constraints, such as refinery turnaround schedules that do not align with peak demand, operational disruptions (e.g., emergency shutdowns), and inaccurate forecasting methods. Key solutions for improvement include: 1) Implementation of the hybrid forecasting method, and 2) challenge sessions to validate planning data. Synchronizing turnaround schedules with seasonal demand and implementing IoT and AI-based digital preventive maintenance are also key solutions. Other solutions include adjusting KPIs and SLAs from M+3 to M+1 and updating SOPs, as well as conducting regular audits to ensure process consistency and sustainability. To ensure optimal implementation, the following is recommended: Use AI/ML and big data–based modelling tools for real-time forecasting and analysis. Integration of historical, economic, and external data is key to improving prediction accuracy. Using IoT sensors to monitor refinery maintenance and reduce downtime. Optimizing vessels, tanks, and transportation for supply flexibility. Elevating the proficiencies of human resources in the domains of forecasting and supply chain management. Support for top management for strategic alignment and coordination between subholdings. Strengthening the management of inventory and the exchange of data among subordinate units. Ensure implementation aligns with policies and market needs by working in tandem with regulators and key customers.

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