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A predictive intelligent framework for digital twin ready crude palm oil supply planning using seasonal time series decomposition

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ABSTRACT

Crude oil supply planning is critical to ensuring operational continuity and national fuel availability in refinery operations. This study evaluates discrepancies between planned and realized crude arrivals at a refinery and generates forecasts for the subsequent twelve periods to support supply planning decisions. Existing practices, crude scheduling relies on Linear Programming outputs used in the monthly Crude Master Program, resulting in notable deviations, with initial Mean Absolute Percentage Error (MAPE) 34% for heavy crude and 8% for super heavy crude. To improve predictive accuracy, a seasonal multiplicative time-series decomposition method is applied as a computational intelligence component for crude oil forecasting. The proposed approach reduces MAPE to approximately 18% for heavy crude and 7% for super heavy crude, demonstrating substantial improvement in planning accuracy. Forecasting outputs provide predictive insights that enable early detection of potential supply deviations and support proactive crude intake planning. Furthermore, forecasting is conceptualized as a predictive intelligence layer embedded within a Digital Twin–ready decision-support framework, linking physical supply operations with virtual scenario evaluation and managerial planning processes. This study positions forecasting as a predictive intelligence component within a Digital Twin–ready decision support framework, contributing to more intelligent, data-driven, and coordinated crude oil supply management.

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1. Introduction

Crude oil supply planning is a critical operational function in refinery systems, directly influencing production continuity, inventory stability, and national energy availability. Refinery operations remain highly sensitive to planning inaccuracies due to supply constraints, logistics uncertainty, and fluctuating demand patterns. Consequently, mature and reliable planning systems are required to support monthly production scheduling and crude oil intake management. Under existing operational practices, refinery crude oil supply planning relies primarily on Linear Programming (LP) based optimization tools, whose outputs serve as key inputs to the monthly Crude Master Program (CMP). The CMP is supported by Crude Web Stock Simulation tools that monitor inventory conditions and coordinate supply scheduling across multiple stakeholders. While LP provides a structured frame work for optimizing refinery operations, it is inherently dependent on the accuracy of its input assumptions. In practice, discrepancies frequently arise between planned and realized crude arrivals, reducing

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planning reliability and introducing operational risks(Kapustin & Grushevenko, 2023). In this context, forecasting plays a complementary role by providing predictive insights that enhance the quality of supply inputs used within LP-driven planning processes. In recent years, the growing volatility and complexity of crude oil supply chains have accelerated the adoption of intelligent, data-driven decision-support approaches in refinery environments. Forecasting is no longer regarded solely as a statistical estimation tool but increasingly functions as a predictive intelligence mechanism that enables proactive, anticipatory, and scenario-based planning(Rashid & Alnaqbi, 2021)(Zheng et al., 2025).

Forecasting is the art and science of predicting future events (Ilievska, 2025). Within this context, forecasting can be interpreted as a form of computational intelligence, where historical operational data is transformed into actionable predictive knowledge to support decision making. Accurate forecasting facilitates early identification of potential supply deviations, allowing planners to evaluate alternative operational responses before disruptions materialize. When integrated into virtual representations of physical operations, such predictive capabilities support the development of Digital Twin–ready environments, bridging historical data analysis with forward-looking decision-making and strengthening the robustness of crude intake planning. Despite these advances, many refinery planning systems continue to treat forecasting as a standalone analytical activity rather than as an integrated component of intelligent supply chain governance. This fragmentation limits the translation of predictive results into coordinated operational decisions. While previous studies have extensively explored Linear Programming (LP) for refinery production optimization and decomposition methods for general demand forecasting, a significant research gap remains in crude oil supply planning. First, existing literature often treats forecasting as an isolated statistical output, failing to address high deviations in specific feedstocks like heavy and super heavy crude. Second, while Digital Twin concepts are emerging in smart manufacturing, their application as a 'Digital Twin-ready' framework specifically integrating predictive intelligence into formal governance like the Crude Master Program (CMP) remains scarce. Unlike prior research focusing on algorithmic complexity, this study emphasizes functional integration to bridge the gap between pure historical data analysis and proactive operational planning in a Logistics 4.0 ecosystem. While previous studies have extensively explored Linear Programming (LP) for refinery production optimization and decomposition methods for general demand forecasting, a significant research gap remains in the functional synchronization of these methods within crude oil supply planning.First, existing literature often treats forecasting as an isolated statistical output. Research by Samari et al. (2022) demonstrates the efficacy of multiplicative decomposition in commercial sectors, yet its application in the high-stakes crude oil industry remains under-explored. Current refinery practices often rely on static outputs which fail to address high deviations in specific feedstocks like heavy and super-heavy crude. There is a critical lack of frameworks that translate "statistical error" into "operational risk mitigation" within the complex logistics of refinery supply chains.

Second, there is a conceptual-to-functional gap in the adoption of Logistics 4.0. While (Iqbal et al., 2026) (Hananto & Veza, 2025; Weis et al., 2025)have established the theoretical importance of Digital Twins and Cyber-Physical Systems for smart manufacturing, their practical application as a 'Digital Twin-ready' framework specifically one that integrates predictive intelligence into formal governance like the Crude Master Program (CMP) remains scarce. Prior research frequently emphasizes algorithmic complexity (e.g., Deep Learning) which often acts as a "black box," making it difficult for industry practitioners to validate and integrate into existing decision-making protocols.This study strengthens the literature by positioning Seasonal Time Series Decomposition not just as a statistical tool, but as a transparent computational intelligence component. Unlike prior research focusing solely on model accuracy, this study emphasizes functional integration to bridge the gap between pure historical data analysis and proactive operational planning. This approach ensures that the predictive insights are "Digital Twin-ready," providing a scalable foundation for future real-time synchronization in a Logistics 4.0 ecosystem.Addressing this gap requires not only improved forecasting accuracy but also a structured architectural integration that connects predictive analytics with managerial planning processes.

Motivated by this challenge, this study evaluates discrepancies between planned and realized crude oil arrivals for heavy and super heavy crude feedstocks using operational data from a refinery company. A seasonal multiplicative time-series decomposition method is applied to enhance forecasting accuracy and reduce planning deviations, as measured by Mean Absolute Percentage

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Error (MAPE). The time series method is an appropriate approach for predicting demand, as past demand patterns have been relatively consistent and accurate over a long period and continue to increase each year (Boyko, 2023; Torres et al., 2021).

Beyond quantitative performance improvement, this research conceptualizes forecasting as a lightweight computational intelligence layer embedded within a Digital Twin–ready decision-support framework aligned with the Crude Master Program. The contributions of this study are threefold. First, it provides an empirical assessment of planning deviations in refinery crude oil supply operations based on real industrial data. Second, it demonstrates the effectiveness of seasonal multiplicative decomposition forecasting in improving prediction accuracy for heavy and super heavy crude feedstocks. Decomposition is a forecasting technique that identifies the factors that affect values in a time series by multiplying the trend fluctuation value by the cycle fluctuation index value (Dudek, 2023; Samari et al., 2022). Third, it proposes a Digital Twin–ready decision-support architecture that positions forecasting as a predictive intelligence component linking physical supply operations with virtual scenario evaluation and governance-level planning. The concept of a Digital Twin has gained significant attention in recent years as a key enabler of intelligent and data-driven systems in complex industrial environments. A Digital Twin can be conceptually defined as a virtual representation of a physical system that is continuously updated using real operational data, enabling monitoring, analysis, and predictive decision-making (Grieves & Vickers, 2016). In the context of energy and supply chain systems, Digital Twins are not merely static simulation models, but dynamic decision-support artifacts that reflect the evolving state of physical operations (Tao et al., 2019). This paradigm allows organizations to bridge historical data analysis with forward-looking planning, particularly in environments characterized by high uncertainty and operational risk, such as crude oil supply chains.

Within a Digital Twin framework, forecasting plays a central role as a predictive engine that anticipates future system states based on historical patterns and contextual information. Traditional forecasting methods provide baseline estimations; however, machine learning–based forecasting enhances this capability by capturing non-linear relationships, complex temporal dependencies, and the influence of exogenous variables (Torres et al., 2021). As a result, ML-based forecasting supports the transformation of Digital Twins from descriptive models into predictive and prescriptive systems (Ivanov et al., 2019). In energy supply chains, accurate forecasting enables early identification of demand–supply imbalances, shipment delays, and inventory risks, which are critical to maintaining operational continuity in refineries. Furthermore, integrating Digital Twin concepts with intelligent forecasting directly contributes to supply chain resilience and scenario-based decision-making. By embedding forecasting outputs into a virtual representation of the supply chain, organizations can simulate alternative scenarios, such as delayed shipments, supplier disruptions, or fluctuating demand patterns, before these events occur in the physical system (Ivanov, 2018; Majstorović, 2022). This capability allows decision-makers to evaluate mitigation strategies proactively, reducing reliance on reactive planning. Consequently, Digital Twin–enabled forecasting supports decision-support systems that enhance the robustness, adaptability, and sustainability of energy supply chain operations. In this regard, forecasting accuracy is not only a performance metric but also a foundational element for developing Digital Twin–ready architectures in crude oil supply planning(Khan et al., 2024). Through this integration, the study advances forecasting from a standalone analytical tool to a functional element of intelligent, data-driven crude oil supply chain management aligned with Supply Chain and Logistics 4.0 principles.

2. Methods

This study adopts an applied computational intelligence methodology to evaluate crude oil supply planning performance and develop a Digital Twin–ready forecasting frame work for refinery operations. The overall research workflow is illustrated in **Fig. 1** and consists of problem identification, data acquisition, pre-processing, forecasting, accuracy evaluation, and decision-support integration. The research begins with problem identification conducted in the production and inventory management domain, focusing on heavy and super-heavy crude oil supply at Refinery Unit. Field observations were performed to understand operational processes related to crude procurement, storage, and scheduling. Historical operational data comprising planned and realized crude oil arrivals were collected for monthly periods. These datasets form the primary in puts for forecasting and

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evaluation (Iyadunni Adewola Olaleye et al., 2024). To complement quantitative data, expert interviews were conducted with supply chain practitioners directly involved in crude oil supply operations. In addition, a literature study was performed using company historical records, textbooks, and scientific journals to establish methodological foundations and contextualize the forecasting approach within supply chain planning research. Data pre-processing was conducted to ensure consistency and reliability of time-series inputs. This stage included data cleaning, validation, and structuring into monthly time-series format. Seasonal pattern identification was performed using autocorrelation analysis in IBM SPSS, followed by seasonal index computation. Trend components were estimated through regression analysis implemented in Microsoft Excel. These steps enable decomposition of the original series into seasonal and trend elements. Forecasting was subsequently performed using a seasonal multiplicative decomposition method. This approach was selected to capture both recurring seasonal patterns and long-term trends in crude oil arrivals. Based on the decomposed components, crude oil supply forecasts were generated for the subsequent 12 periods. Forecast accuracy was evaluated using MAPE, comparing baseline planning performance derived from the Crude Master Program with results obtained after applying the proposed forecasting method.

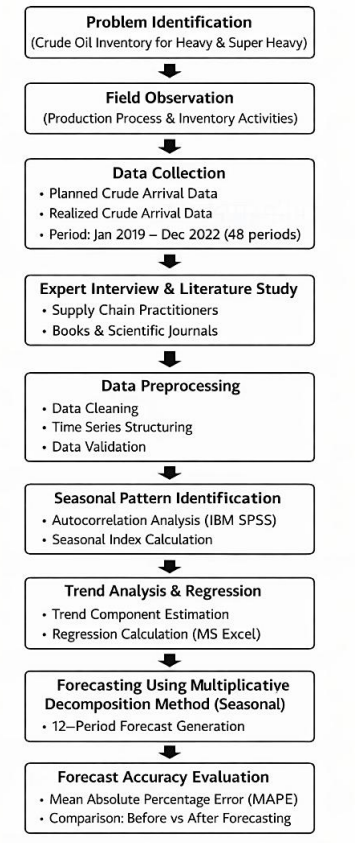


Fig. 1 Flow process research.

2.1. Mathematical Formulation of Seasonal Multiplicative Decomposition

The seasonal multiplicative decomposition method is employed to analyze the crude oil arrival time series by isolating its constituent components, providing a transparent mechanism for predictive intelligence (Klaar et al., 2023). In this model, the observed arrival value (Y_t) at time t is expressed as the product of its underlying components. For medium-term refinery supply planning, the formulation is defined as follows:

$$y_{t=T_t\ X\ S_t\ X\ I_t} \quad (1)$$

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Where:

- Y_t =Predicted crude oil arrival volume at period t.
- T_t =The trend component, representing the long-term direction of the data.
- S_t =The seasonal index, reflecting recurring patterns within a 12-month cycle.
- I_t =The irregular or random component.

2.1.1. Trend Estimation T_t

The trend component is estimated using the Ordinary Least Squares (OLS) regression method to determine the linear relationship between time (t) and arrival volume. The linear trend equation is defined as:

$$T_{t=a+bt} \quad (2)$$

2.1.2. Seasonal Index Calculation (St)

The seasonal component is identified through autocorrelation analysis. The seasonal index (St) is calculated using the ratio-to-moving average approach, where the original data is divided by the Centred Moving Average (CMA) to remove trend and cyclical influences. The normalized seasonal index is then used to adjust the trend forecast to reflect seasonal fluctuations

2.1.3. Forecast Accuracy Evaluation

To evaluate the effectiveness of the proposed framework, the Mean Absolute Percentage Error (MAPE) is used as the primary performance metric. This metric compares the discrepancies between the planned values from the Master Program and the forecasted values against the actual realized arrivals. The MAPE formula is expressed as:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \ddot{Y}_t}{Y_t}\right| x\ 100\ \% \quad (3)$$

where Y_t represents the actual realized arrival $\hat{y}_t$is the forecasted or planned value, and n is the number of periods.

3. Results and Discussion

This study evaluates discrepancies between planned and realized crude oil arrivals for heavy (H) and super-heavy (SH) crude over 48 monthly periods, as summarized in Table 1. Initial assessment using Mean Absolute Percentage Error (MAPE) shows significant deviation for heavy crude (34.54%) and lower deviation for super-heavy crude (8.71%) on Table 1, indicating inconsistent planning reliability, particularly for heavy crude.

Table 1 Master program MAPE score

Heavy	34.54%
Super Heavy	8.71%

Therefore, the authors apply the multiplicative decomposition forecasting method and evaluate crude oil arrivals to identify the causes of discrepancies between the arrivals of heavy and super-heavy crude, aiming to achieve lower error values than the previous year. The data pattern must be defined first in the forecasting calculation process. At this stage, the author uses IBM SPSS software on the autocorrelation menu and Microsoft Excel on the regression menu. The results of the autocorrelation analysis show that the data have a random-seasonal pattern, with an ACF peak at

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several periods, as shown in **Fig 2**. Therefore, the multiplicative decomposition method corrects for the available data.

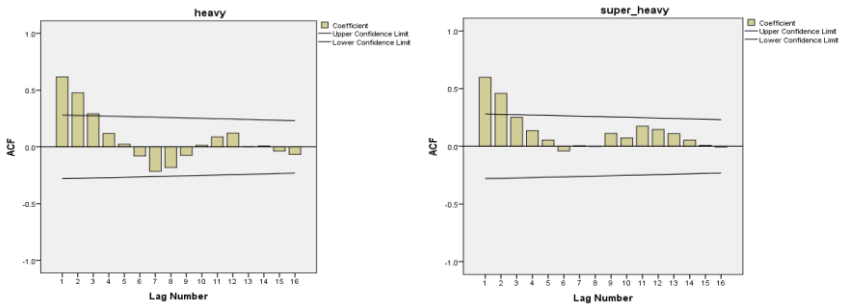


Fig. 2 Result trend autocorrelation.

After identifying the pattern, forecast using the seasonal multiplicative decomposition method until the SAF value is obtained as the Seasonal Index (SI) for the two types of crude oil. Then, create an equation for the trend index decomposition of the original data using the regression feature in Ms. Excel, aiming to minimize errors and maximize R-squared. This is shown in **Fig 3**.

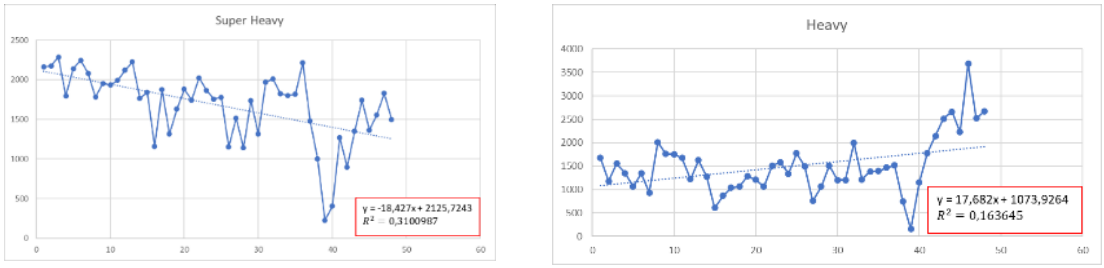


Fig. 3 Equation for trend component decomposition.

These results demonstrate that the proposed method effectively reduces planning deviations, especially for crude types exhibiting higher variability. A comparison between realized demand and forecasted values is illustrated in **Fig. 4**, compares forecasting results with data on the realized need for super-heavy and heavy crude over the past four years.

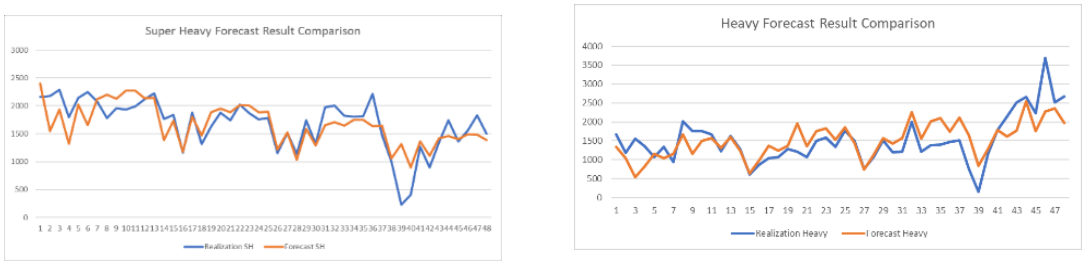


Fig. 4 Super heavy forecast result comparison.

After applying the seasonal multiplicative decomposition method, forecasting accuracy improved substantially. MAPE for heavy crude decreased to 18.43%, while super heavy crude improved marginally to 7.61%, as presented in **Table 2**. Beyond numerical accuracy, forecasting outputs provide predictive insights into future supply conditions, enabling early identification of potential overstock or shortage risks.

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Table 2 Comparison of MAPE before and after using the forecast decomposition method, multiplicative

Crude Type	Plan from the Master Program	Plan used Forecast Decomposition Multiplicative
Heavy	34.54	18.43
Super Heavy	8.71	7.61

Within a Digital Twin–ready environment, the improved forecasting accuracy obtained from the multiplicative decomposition method can be interpreted beyond numerical performance indicators such as MAPE. The forecasting results provide predictive insights into future crude oil supply conditions, allowing planners to anticipate potential deviations between planned and realized crude arrivals as **Table 3.** These predictive insights serve as critical inputs for scenario-based simulation, where alternative supply conditions, such as shipment delays or inventory imbalances, can be evaluated in a virtual planning context without directly affecting physical operations. Furthermore, the forecasting outputs function as an early warning mechanism for potential carry-over risks and supply delays, particularly during periods of high operational uncertainty. By embedding forecasting results into the Crude Master Program's decision-making process, refinery management is better equipped to shift from reactive responses to proactive, anticipatory planning. As a result, the forecasting model contributes not only to improved prediction accuracy but also to enhanced decision support capabilities within a Digital Twin–ready crude oil supply planning framework.

Table 3 Interpretation of forecasting results for decision support in crude oil supply planning

Forecasting Output	Observed Pattern/ Result	Operational Interpretation	Decision Support Implication (CMP Context)
Forecasted crude arrival volume	Increasing or decreasing trend over the forecast horizon	Indicates potential overstock or shortage risk	Adjustment of crude intake plan and inventory level
Seasonal peak forecast	Recurrent increase in specific periods	High demand or intensive operation periods	Buffer stock preparation and supply scheduling
Forecast deviation (plan vs realization)	Persistent gap in selected periods	Potential logistics delay or supplier disruption	Early rescheduling and coordination during CMP
High MAPE before forecasting	Low planning accuracy	Reactive decision-making tendency	Need for improved predictive planning
Reduced MAPE after forecasting	Improved prediction accuracy	More reliable demand–supply estimation	Stronger basis for proactive CMP decisions

The forecasting intelligence layer enables planners to detect potential deviations between planned and realized crude oil arrivals before they occur. This early warning capability is essential in crude oil logistics, where shipment delays, capacity constraints, and supplier variability can lead to cascading operational impacts. By identifying deviation risks in advance, forecasting supports a shift from reactive corrective actions to proactive, anticipatory planning, a defining characteristic of intelligent logistics systems. Importantly, intelligence in this study is not defined solely by algorithmic complexity. While advanced machine learning models are often associated with intelligent systems, this research demonstrates that intelligence can also emerge through functional integration. By systematically linking forecasting outputs to decision-making activities within the Crude Master Program, predictive insights are translated into actionable planning adjustments. This articulation emphasizes that intelligent behavior in supply chain systems can be achieved through the structured use of predictive information, even when classical forecasting methods are employed.

Deepened Analysis and Literature Positioning

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The implementation of the Seasonal Multiplicative Decomposition method demonstrates a transformative improvement in forecasting accuracy. As shown in the performance metrics, the Mean Absolute Percentage Error (MAPE) for Heavy Crude was significantly reduced from 34% to 18%, while Super Heavy Crude improved from 8% to 7%.

Analysis of Forecasting Performance and Practical Implications

The core strength of this framework lies in its ability to deconstruct crude oil arrival fluctuations, proving they are not merely stochastic (random) but possess discernible seasonal patterns previously overlooked by the Linear Programming (LP)-based systems. In the case of Heavy Crude, the initial high deviation (34%) suggests that the existing monthly planning was "blind" to cyclical logistical bottlenecks and production schedules in the countries of origin.

By isolating the seasonal component (S_t), the proposed framework acts as a Predictive Intelligence (PI) buffer. This enables the refinery to transition from a reactive "wait-and-see" approach to a proactive "predict-and-prepare" strategy. This finding extends the work of Samari et al. (2022), who demonstrated the effectiveness of decomposition in commercial demand; however, this study proves that in the high-volatility energy sector, the method's value lies in its interpretability allowing planners to see the 'why' behind the numbers, which is often lost in complex machine learning models.

Comparison with Prior Studies and Theoretical Positioning

This research offers a more proactive stance compared to the supply chain resilience models discussed by Ivanov (2018). While Ivanov emphasizes mitigation *after* disruptions occur, the integration of predictive intelligence into the Crude Master Program (CMP) governance allows for preventive action before supply gaps impact refinery operations.

Furthermore, these results validate the theoretical framework of Tao et al. (2019) regarding the evolution of Digital Twins. By achieving a stable MAPE of 7% for Super Heavy Crude, this study establishes a high-fidelity "historical twin" of the physical supply chain. The transformation of CMP from a static document into a dynamic, responsive system demonstrates a practical application of Logistics 4.0, where mathematical precision and governance framework converge to create a "Digital Twin-ready" environment.

Clarification of the Role of Experts in Model Validation

A critical nuance in this study is that the model's validity is not derived solely from statistical metrics but through a Hybrid-Intelligence validation process. While the decomposition algorithm identifies patterns, industry experts from the petrochemical sector were instrumental in contextualizing data anomalies. For instance, experts validated whether deviations in the last 12 periods were "structural" (e.g., permanent port facility upgrades) or "temporary". This expert-in-the-loop approach ensures that the "Digital Twin" remains grounded in physical reality. This synergy between computational intelligence (algorithms) and human intelligence (domain expertise) addresses a common criticism of automated systems in Industry 4.0, providing a more robust and ethically verifiable decision-making framework for national fuel security.

To further align with the principles of Supply Chain and Logistics 4.0, the proposed forecasting approach is positioned within a Digital Twin–ready supply chain architecture. A Digital Twin–ready system establishes a structured foundation that enables future integration of real-time data acquisition, simulation, and optimization without requiring a full Digital Twin implementation at this stage. In this architecture, the physical layer represents actual crude oil supply operations at Refinery Unit, including procurement planning, inventory management, storage capacity, and logistics activities. Operational data generated from this layer is consolidated in a data integration layer, where historical consistency and data reliability are ensured. The forecasting intelligence layer processes this data to create predictive insights regarding future crude oil arrivals and potential planning deviations. Forecasting outputs are then mapped onto a virtual representation of the crude oil supply system, functioning as a simplified Digital Twin. Within this virtual environment, planners can evaluate alternative supply scenarios, such as seasonal demand fluctuations or delayed shipments, without direct intervention in physical operations.

Finally, the decision-support layer integrates forecasting-driven insights into managerial processes, particularly within the Crude Master Program, supporting coordinated adjustments to crude intake

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planning and logistics scheduling. By embedding forecasting within a Digital Twin–ready architecture, this study explicitly positions crude oil supply planning within the Logistics 4.0 framework, emphasizing predictive control, enhanced visibility, and intelli-gent decision support. This positioning elevates the research's contribution beyond improving forecasting accuracy, demonstrating its relevance to the design of innovative, resilient, and data-driven supply chain systems.To provide a system-level interpretation of how forecasting results support decision-making, this study proposes a Digital Twin–ready supply chain architecture. The architecture conceptualizes forecasting as a predictive intelligence layer that links physical crude oil supply operations with virtual scenario evaluation and governance-level decision support.

The improvement in forecasting accuracy, as reflected in the reduction of Mean Absolute Percentage Error (MAPE) values after applying the seasonal multiplicative decomposition method, provides a quantitative foundation for interpreting forecasting as a predictive intelligence component within the proposed Digital Twin–ready architecture. While MAPE is commonly used as a statistical measure of forecasting performance, in the context of intelligent supply chain systems, improved forecasting accuracy also enhances the reliability of decision-support mechanisms that depend on predictive insights. In this study, intelligence is defined in terms of functional integration and decision-support capability rather than algorithmic complexity, emphasizing how forecasting outputs are embedded into coordinated planning and governance processes. Within the proposed architecture illustrated in **Fig 5**, reducing MAPE values directly strengthens the Forecasting Intelligence Layer, which serves as the system's analytical core. Lower forecasting errors indicate greater confidence in predicted crude oil arrival volumes, enabling planners to anticipate potential deviations between planned and realized supply with greater precision. These predictive insights serve as early warning signals that support proactive adjustments in crude oil intake planning, particularly under conditions of logistics uncertainty and capacity constraints.



Fig. 5 Digital Twin–ready architecture for intelligent crude oil supply chain planning.

The integration of forecasting outputs into the Virtual Supply Chain Twin allows these improved predictions to be interpreted beyond numerical indicators. Forecasted crude arrival volumes and deviation patterns can be mapped onto a virtual representation of the crude oil supply chain, enabling planners to evaluate alternative scenarios, such as delayed shipments, seasonal demand peaks, or carry-over risks. This scenario evaluation capability supports decision-makers in understanding the operational implications of forecasting outcomes before they materialize in physical operations. At the governance level, forecasting-driven insights are systematically incorporated into the Crude Master Program (CMP), which functions as the primary decision-support and coordination forum for crude oil supply planning. The improved MAPE performance enhances the credibility of forecasting results used during CMP discussions, enabling more informed planning adjustments, coordination across supply chain actors, and mitigation of deviation risks. In this sense, improvements in forecasting accuracy translate into tangible decision-support value rather than remaining isolated analytical achievements.

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Overall, the linkage between improved MAPE values, the Digital Twin–ready architecture, and CMP decision-making demonstrates how quantitative forecasting performance contributes to intelligent supply chain and logistics planning. By embedding forecasting results within a structured system architecture, this study advances forecasting from a standalone analytical activity to a predictive intelligence mechanism that supports coordinated, proactive, and data-driven crude oil supply chain governance aligned with Supply Chain and Logistics 4.0 principles.

4. Conclusion

This study evaluates crude oil supply planning performance at a refinery company and identifies significant discrepancies between planned and realized crude arrivals, particularly for heavy crude feedstock. Initial Mean Absolute Percentage Error (MAPE) values indicated substantial planning deviations, reaching 34.54% for heavy crude and 8.71% for super heavy crude. By applying a seasonal multiplicative time-series decomposition method, forecasting accuracy improved considerably, reducing MAPE to 18.43% for heavy crude and 7.61% for super heavy crude. These results demonstrate the effectiveness of the proposed approach in enhancing prediction reliability and mitigating planning deviations in refinery supply operations.

Beyond numerical improvements, this research advances a system-level perspective by framing forecasting as a predictive intelligence component embedded within a Digital Twin–ready decision support framework. The integration of forecasting outputs into the Crude Master Program enables early detection of supply deviations, supports proactive scheduling adjustments, and strengthens coordination across crude oil supply chain actors. Rather than treating forecasting as an isolated analytical task, this study demonstrates how predictive information can be operationalized to support anticipatory planning and governance. Importantly, computational intelligence in this work is defined in terms of functional integration and decision-support capability rather than algorithmic complexity. While advanced machine learning techniques are not implemented, the structured use of seasonal time-series forecasting within a Digital Twin–ready architecture establishes an effective predictive intelligence layer for refinery supply planning. This approach illustrates how classical forecasting methods, when systematically embedded into virtual system representations and managerial processes, can contribute to intelligent, datadriven logistics operations.

The proposed architecture provides a foundation for future extensions toward realtime Digital Twin implementations, including integration of machine learning–based forecasting, sensor-driven data acquisition, and prescriptive optimization. As such, this research contributes not only to improved crude oil forecasting accuracy but also to the development of computationally enabled, resilient, and proactive supply chain systems aligned with Supply Chain and Logistics 4.0 principles.

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