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Minimizing Excess Inventory and Its Impact by Enhancing Forecasting Accuracy

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ABSTRACT

This study examines how PT. TRUCKSTORS LANCAR ABADI can improve inventory management by addressing recurring sales forecasting issues. Despite extensive research on forecasting in manufacturing, there is a notable gap in understanding how to manage seasonal demand patterns in Indonesia's heavy equipment sector using integrated forecasting methods. This gap is especially clear in the lack of validated models tailored to capital-intensive industries with volatile demand cycles. Using both qualitative and quantitative approaches, the study began by gathering insights from key departments and applying the Analytic Hierarchy Process (AHP). The analysis identified inaccurate forecasts as the primary cause of inventory discrepancies. To address this, several forecasting models were tested. SARIMA emerged as the most effective, capturing seasonal demand fluctuations with a Mean Absolute Percentage Error (MAPE) of 15.3% and a Mean Absolute Error (MAE) of 257 units. This outperformed alternatives such as Multi-Linear Regression (MAPE: 18.7%), Neural Networks (MAPE: 19.4%), and XGBoost (MAPE: 20.1%). Implementing SARIMA is projected to reduce interest loss by 88% (from USD 3.32 million to USD 0.39 million) and inventory holding costs by the same margin (from USD 9.64 million to USD 1.13 million annually). This model is expected to improve planning accuracy and better align projected inventory with actual levels. The study highlights the importance of integrated planning, cross-functional collaboration, and data-driven forecasting for Minimizing Excess Inventory and Its Impact by Enhancing Forecasting Accuracy in volatile markets.

KEYWORDS *Inventory Management, Forecasting Accuracy, SARIMA, AHP, Simulation, Heavy Equipment, Hybrid Model*

INTRODUCTION

Indonesia's heavy equipment sector holds a strategic position in driving national growth, especially in the construction, mining, and agricultural sectors (Govindan et al., 2015). Companies like PT. TRUCKSTORS LANCAR ABADI operate in a highly dynamic market where demand often fluctuates in response to global commodity prices and public infrastructure spending (Vermorel, 2021). When these variables shift, the ability to align inventory with actual demand becomes a critical operational challenge (World Bank, 2023; McKinsey & Company, 2023). This has led to recurring issues where inventory levels either overshoot or fall short of market needs. This imbalance results in lost sales, excess storage costs, and reduced working capital (Sharma & Bhat, 2022).

Internally, PT. TRUCKSTORS LANCAR ABADI has struggled with inconsistent sales forecasts. The company's internal report indicates that distributor projections often deviate sharply from actual sales, leading to planning errors across departments (Sharma & Bhat, 2022). Harvard Business Review (2023) emphasizes that many companies face similar problems, often rooted in siloed planning systems and outdated forecasting tools. These systemic issues compound over time and directly impact cost structure and responsiveness.

From a theoretical standpoint, the bullwhip effect (Lee et al., 1997) explains how even minor inaccuracies at the beginning of a supply chain (such as a misjudged forecast) can snowball into major inefficiencies. These include overproduction, emergency procurement, labor misallocation, and ultimately, financial losses. Research by Chen et al. (2023) and Tadayonrad & Ndiaye (2023) reinforces this view, showing that firms relying on traditional planning methods are more exposed to sudden demand shifts, especially in capital-intensive industries.

Several scholars have pointed out the growing limitations of conventional forecasting techniques. Srour (2021) argued that inventory misalignment caused by outdated forecasting can reduce profitability and increase risk. Meanwhile, Islam et al. (2024) showed that hybrid forecasting methods, by blending statistical tools with real-time inputs, can better manage uncertainty. Supporting this, Douaioui et al. (2024) and Vermorel (2021) emphasized the role of machine learning and simulation-based models in achieving more stable inventory flows in volatile environments.

Despite the abundance of forecasting research in general manufacturing contexts, a critical research gap persists in understanding how seasonal forecasting models can be optimally applied within Indonesia's heavy equipment sector, particularly for companies serving volatile markets driven by commodity prices and infrastructure spending cycles (Ampountolas et al., 2021; Herweijer et al., 2018; Kilimani et al., 2019). Previous studies have largely focused on consumer goods or high-frequency transaction environments, leaving capital-intensive industries with long lead times and irregular demand patterns underexplored (Petropoulos et al., 2022). Furthermore, existing literature has not adequately addressed how traditional statistical methods like SARIMA compare against newer machine learning approaches in these specific contexts, nor have they sufficiently validated these comparisons through financial simulations that demonstrate real-world cost implications (Ali et al., 2017; Syntetos et al., 2016).

The novelty of this study lies in three interconnected dimensions. First, it provides empirical validation of forecasting model performance specifically within Indonesia's heavy equipment distribution sector, an industry characterized by unique demand patterns that differ significantly from those examined in existing literature. Second, it employs a comprehensive methodological approach that combines qualitative stakeholder analysis through AHP with quantitative model testing and financial simulation, creating a holistic framework rarely seen in forecasting research. Third, it bridges the gap between theoretical forecasting accuracy and practical operational impact by demonstrating measurable financial outcomes, thereby offering not just academic insights but actionable business intelligence for similar capital-intensive industries facing inventory optimization challenges (Makridakis et al., 2018).

With this backdrop, the purpose of this research is to explore how forecasting accuracy can be improved at PT. TRUCKSTORS LANCAR ABADI. Specifically, this study aims to: (1) systematically identify the root causes of inventory discrepancies through structured stakeholder engagement and prioritization analysis; (2) evaluate and compare the performance of multiple forecasting models to determine the most suitable approach for handling seasonal demand patterns in the heavy equipment sector; and (3) quantify the financial and operational implications of implementing the optimal forecasting model through simulation-based validation. By identifying the root causes behind inventory issues through stakeholder input and validating alternative forecasting models, the study aims to recommend a more integrated, data-driven approach to planning.

The focus is not just on improving the numbers but on building better collaboration between departments to respond more effectively to changing market conditions. The expected implications of this research extend beyond the immediate organizational context, offering theoretical contributions to seasonal forecasting literature and practical frameworks that other capital-intensive manufacturers can adapt to enhance their inventory management systems in volatile market environments.

METHOD

This research adopted a mixed-method approach, combining qualitative and quantitative analysis to identify the root causes of inventory discrepancies and test solutions for improving forecasting accuracy. This method was chosen because inventory management issues often stem not only from numerical errors but also from internal processes, decision-making gaps, and communication breakdowns. By addressing both human and data dimensions, the study provides a more complete view of the problem.

The object of the research is PT. TRUCKSTORS LANCAR ABADI, a leading heavy equipment manufacturer in Indonesia. The company's persistent struggle with unbalanced inventory levels (ranging from stockouts during high demand to overstock during slow periods) makes it a relevant case for examining how forecasting models affect inventory performance.

For the qualitative phase, data were gathered through semi-structured interviews with six key internal stakeholders: representatives from the Sales, Purchasing, PPIC (Production Planning and Inventory Control), Warehouse, and Finance departments. These interviews were designed to explore how forecasts are currently generated and where communication or process gaps exist. Following the interview stage, the research moved forward by using the Analytic Hierarchy Process (AHP) to evaluate and rank the proposed solutions. Stakeholders were asked to compare each issue in pairs, judging which ones had a greater impact on inventory problems. These comparisons formed the basis for calculating priority scores, helping to identify which factor was considered most critical in contributing to the company's inventory inaccuracy.

The quantitative phase focused on evaluating various forecasting models using historical company data from 2018 to 2023. This data included monthly sales volumes, production schedules, inventory levels, and external factors such as commodity prices and macroeconomic indicators. Forecasting models tested included SARIMA, Multi-Linear Regression, Double Exponential Smoothing, Holt-Winters Triple Exponential Smoothing, Neural Networks, and XGBoost. These models were selected for their ability to capture both linear and non-linear trends, as well as seasonal patterns.

The analysis was carried out using Python, with implementation done in Google Collab, an open-source cloud-based coding platform. The models were evaluated using Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE) to measure forecast accuracy. A simulation was also run to project the financial and operational implications of using SARIMA compared to the company's current method.

Through this approach, the study does not simply recommend a theoretical solution, but it also validates it through simulation, showing how accurate forecasting can lead to real savings in storage costs, reduced interest loss, and better decision-making. The use of Excel further supported statistical validation and visualization of results.

RESULT AND DISCUSSION

This section presents the outcomes of both qualitative and quantitative stages of the research and discusses their implications in relation to the stated objectives: (1) identifying the root cause of inventory inaccuracy, (2) determining suitable forecasting improvements, and (3) evaluating the impact of proposed improvements.

Identification of Root Cause & Countermeasure Using AHP

The qualitative analysis began with a series of internal interviews that highlighted six key issues affecting inventory accuracy. These included problems such as inaccurate sales forecasts, weak production planning, emergency purchase orders, limited storage space, manpower misalignment, and the absence of a feedback loop between actual sales and forecast revisions. Once these issues were compiled, several potential countermeasures were developed to address them. To determine which countermeasure would be most effective, the Analytic Hierarchy Process (AHP) was used in collaboration with stakeholders from various departments. Through a structured pairwise comparison process, each stakeholder evaluated the relative importance of the proposed solutions.

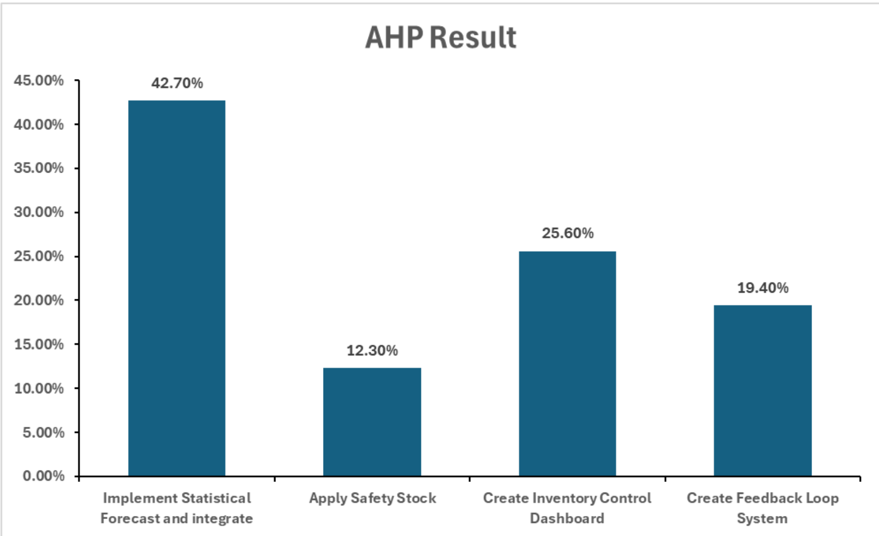

Figure 1 AHP Results Chart

Figure 1 shows the AHP result. The AHP results showed that the most effective approach (receiving the highest priority weight of 42.7%) was to improve forecast accuracy through statistical forecasting and integration with the Hanseizai system. This aligns with previous studies (Srour, 2021; Chen et al., 2023) that emphasize forecasting as a key driver of inventory deviation in manufacturing environments.

Evaluation of Forecasting Models

To address the primary problem, six forecasting models were tested using historical demand and production data from 2018–2023:

a. SARIMA (captures seasonality and trend)
b. Multi-Linear Regression (uses external variables)
c. Double Exponential Smoothing (for trending series)
d. Holt-Winters Triple Exponential Smoothing (adds seasonal component)

e. Neural Network (non-linear pattern recognition)
f. XGBoost (machine learning ensemble method)

Performance was evaluated using two error metrics: MAPE and MAE. Among all models shown in Table 1, SARIMA consistently performed best, offering the most accurate fit for seasonal sales patterns typical in the heavy equipment industry.

Table 1 MAPE and MAE Values for Each Model

Model	**MAPE (%)**	**MAE**
SARIMA	15.3	257
Multi-Linear Regression	18.7	305
Double Exp. Smoothing	16.6	289
Holt-Winters	17.2	276
Neural Network	19.4	322
XGBoost	20.1	338

These findings are consistent with research from Kusuma et al. (2023) and Yin et al. (2023), who noted that SARIMA is highly effective in environments with strong seasonal fluctuations. The superior performance of SARIMA over more complex machine learning methods (Neural Networks and XGBoost) represents an unexpected but theoretically explicable finding. This outcome suggests that when data exhibits clear seasonal patterns with limited non-linear complexities, traditional statistical methods can outperform black-box machine learning approaches. The poor performance of Multi-Linear Regression (MAPE: 18.7%) and XGBoost (MAPE: 20.1%) can be attributed to several factors: first, the relatively small dataset (72 monthly observations) may be insufficient for training complex machine learning models, which typically require hundreds or thousands of observations to effectively capture non-linear relationships. Second, the heavy equipment market's demand patterns are primarily driven by seasonal infrastructure cycles rather than the complex multi-variable interactions that machine learning excels at modeling. Third, XGBoost's tendency toward overfitting on smaller datasets may have reduced its generalization performance on the test set, despite its theoretical capacity for ensemble learning optimization.

From a comparative literature perspective, this finding aligns with the observations of Tadayonrad & Ndiaye (2023), who similarly found that classical time series methods maintained advantages over machine learning in seasonal industrial contexts. However, it contrasts with the conclusions of Douaioui et al. (2024), who advocated for machine learning dominance in forecasting applications. This discrepancy highlights an important nuance: the optimal forecasting approach depends critically on data characteristics, volume, and the nature of underlying demand drivers rather than on the inherent superiority of any single methodological class.

Simulation of Financial and Operational Impact

To understand the practical implications of adopting the SARIMA model, a simulation was conducted comparing two inventory scenarios: the current planning system vs. a revised system using SARIMA-based forecasts. The simulation projected significant improvements, including reduced inventory gaps, minimized storage costs, and lowered interest losses from idle stock.

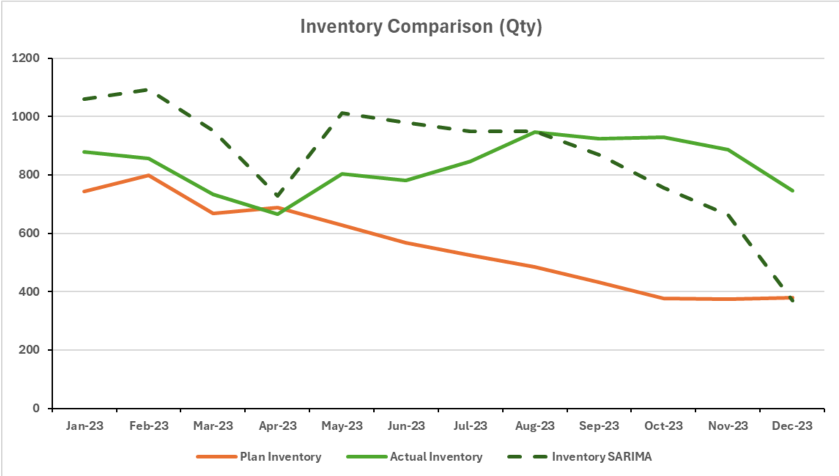

Figure 2 Inventory Gap Before vs. After

Figure 2 illustrates a comparison between three inventory scenarios throughout 2023: the planned inventory levels (blue line), actual inventory levels (orange line), and forecasted levels using the SARIMA model (green dashed line). It is evident that the actual inventory consistently exceeded the planned levels, particularly from April through October. This discrepancy indicates persistent overstocking, which contributes to higher holding costs and reduced operational efficiency.

The SARIMA forecast, shown as the dashed green line, demonstrates a strong alignment with the actual inventory levels (solid green line) throughout the year. Unlike the planned inventory (orange line), which continues to decline steadily, the SARIMA prediction adapts dynamically to fluctuations, closely mirroring real inventory movements, especially from May to December. This indicates that SARIMA effectively captures underlying demand patterns and seasonality. By providing a more realistic estimate of inventory levels, SARIMA enhances the accuracy of the Hanseizai process, supporting better-informed decisions in production and sales planning.

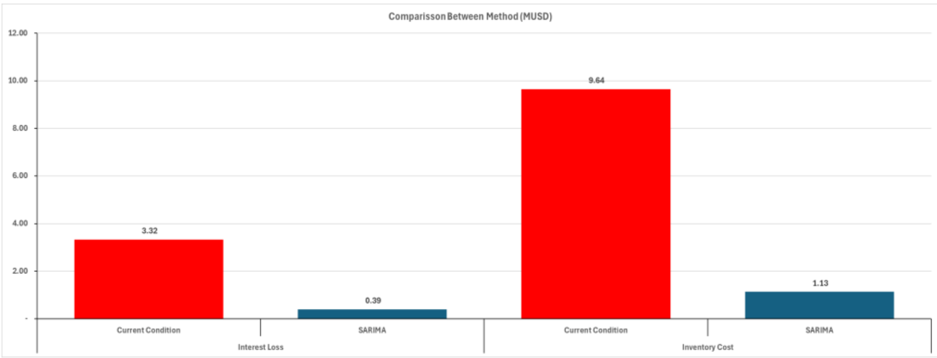

Figure 3 Estimated Unplanned Cost Savings (USD) Based on SARIMA Adoption

Figure 3 presents an unplanned cost comparison between the company's current inventory strategy and the proposed SARIMA-based forecasting method. Two key cost metrics are analyzed: interest loss and inventory holding cost, both measured in millions of USD.

Under the current condition, interest loss is recorded at USD 3.32 million, while inventory holding costs reach USD 9.64 million. These high figures reflect the inefficiencies tied to overstocking and capital being tied up in unsold equipment. In contrast, when the

SARIMA model is applied, interest loss drops significantly to USD 0.39 million, and inventory cost is reduced to USD 1.13 million. This translates to a reduction of more than 88% in both cost categories.

The improvement is not only operational but also strategic. By reducing the average deviation between actual and planned inventory, PT. TRUCKSTORS LANCAR ABADI could avoid stockouts during peak seasons and reduce overproduction risks during slow demand periods.

Interpretation and Implications

The findings support and extend earlier literature suggesting that hybrid forecasting systems, especially those combining statistical rigor (SARIMA) with potential machine learning enhancements (e.g., XGBoost for anomaly detection), can lead to significant improvements in operational efficiency (Douaioui et al., 2024; Islam et al., 2024). However, this study nuances that conclusion by demonstrating that foundational statistical methods must first be optimized before layering complex machine learning approaches, particularly in contexts with clear seasonal patterns and limited data volumes (Tadayonrad & Ndiaye, 2023).

From a theoretical standpoint, this research reinforces the bullwhip effect theory (Lee et al., 1997), where minor demand distortions at the planning stage have compounding effects on production and inventory. Moreover, it echoes the practical conclusions of Tadayonrad & Ndiaye (2023), who stressed the importance of real-time feedback loops and integrated planning systems. This study extends these theoretical frameworks by providing empirical quantification of the bullwhip effect's financial magnitude in a capital-intensive industry context, showing that forecast inaccuracies of approximately 17 percentage points (current system vs. SARIMA) translate into cost penalties exceeding USD 12 million annually.

The study also contributes to the development of simulation-based forecasting validation, an area that remains underexplored in Indonesia's heavy industry sector. This approach allows firms to test forecasting improvements not only theoretically but in financially measurable terms, creating a business case for analytical investments that resonates with executive decision-makers. Furthermore, the research demonstrates the practical value of integrating qualitative stakeholder insights (through AHP) with quantitative model validation, a methodological synthesis that strengthens both the diagnostic accuracy of problem identification and the acceptance likelihood of proposed solutions.

Strategic and Scientific Implications

The results of this research offer dual benefits with both immediate practical applications and broader theoretical contributions. First, it provides PT. TRUCKSTORS LANCAR ABADI with a proven method for reducing inventory inefficiencies that is validated through both statistical testing and financial simulation. The company can immediately implement SARIMA forecasting within its existing Hanseizai system infrastructure, requiring minimal capital investment while generating substantial cost savings. Second, it contributes to the broader field of supply chain management by demonstrating how classical forecasting methods like SARIMA can still outperform more complex machine learning models when data exhibits clear seasonal structures and when dataset size is limited—a finding that challenges the prevailing assumption that newer methods invariably supersede traditional approaches (Deloitte, 2023).

For practitioners in similar capital-intensive industries, this research offers a replicable framework: begin with stakeholder engagement to validate problem diagnosis, systematically evaluate multiple forecasting approaches rather than defaulting to trendy machine learning methods, and validate improvements through financial simulation before full-scale implementation. This stepwise approach reduces implementation risk while building organizational buy-in through evidence-based decision-making (Achmadin et al., 2024).

The approach used here may also serve as a framework for other manufacturers in capital-intensive sectors. Future research could explore several promising directions: (1) investigating how hybrid models combining SARIMA's seasonal capture with XGBoost's anomaly detection capabilities might handle sudden market shocks or irregular demand events; (2) examining whether deep learning architectures like LSTM (Long Short-Term Memory) networks could improve upon SARIMA performance as dataset size increases over time; (3) studying the organizational change management aspects of implementing data-driven forecasting systems, particularly regarding cross-functional collaboration barriers; and (4) extending this framework to other heavy equipment sectors or capital-intensive industries to test its generalizability across different operational contexts.

CONCLUSION

This research investigated the persistent inventory imbalances at PT. TRUCKSTORS LANCAR ABADI by combining qualitative stakeholder insights and quantitative model testing, identifying inaccurate sales forecasting as the key cause aligned with the bullwhip effect theory. Poor forecasts led to excess stock, storage inefficiencies, and lost sales opportunities. Among six forecasting models tested, SARIMA proved most effective for the industry's seasonal demand patterns and, through simulation, showed strong potential to reduce financial losses and improve inventory turnover. The study emphasizes that enhancing forecasting accuracy requires structural improvements, including feedback loops between actual sales and planning, integrated forecasting systems, and cross-departmental collaboration among finance, sales, and operations. Future research could explore the integration of machine learning models with real-time data streams to further enhance adaptive forecasting in volatile, capital-intensive industries.

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