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IMPROVING SALES FORECAST ACCURACY USING LEAN SIX SIGMA: A CASE STUDY IN THE FMCG INDUSTRY

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Abstract

Sales forecasting accuracy is crucial for operational efficiency, inventory optimization, and service reliability in commodity and logistics industries. ABC Company faces persistent challenges in achieving reliable forecasts, leading to frequent rescheduling, shipment adjustments, and cross-functional misalignment. This research aims to identify the major factors affecting forecast accuracy at ABC Company, develop solutions to address root causes, and determine the most appropriate forecasting approach. Using the Lean Six Sigma DMAIC framework, it analyzes historical data (Jan 2024-Dec 2025) with MAPE, Forecast Bias, and RMSE metrics. Qualitative data from stakeholder interviews reveal primary drivers: weak forecasting governance, insufficient integration of execution feasibility, lack of stable forecasts, and unstructured expert judgement. The study proposes a four-stream improvement framework focusing on forecast governance stabilization, feasibility integration, quantitative forecast improvement, and structured expert judgement integration via Expert Knowledge Elicitation. A control mechanism with SOPs, RACI, KPI monitoring, and regular reviews ensures sustainable improvement.

Keywords: ***Sales Forecasting, Forecast Accuracy, Lean Six Sigma, DMAIC, Holt-Winters, Expert Knowledge Elicitation, Supply Chain Planning.***

INTRODUCTION

Sales forecasting is a foundational element in supply chain planning which determines the procurement of the raw material, production scheduling, inventory management, and logistics commitment. In commodity based industry where long lead times, volatile demand, and high capital intensity, forecast inaccuracy may results in many problems within the supply chain, excess inventory, underutilized capacity, rising logistic cost, and customer dissatisfaction. FMCG represents one of the most complex industry where the demand is heavily influenced by seasonaliy, lifestyle trend, logistical challenge, and also volatile price fluctuation. At the same time, production are capacity-constrained while outbound logistics also rely on limited shipping availability. With such context, forecasting errors are not merely statistical deviations, but directly affect the feasibility and reliability of the operations. Despite this complexity, forecasting practices in many commodity-based organizations remain heavily reliant on the customer call-off and informal expert's hunch. This approach provides responsiveness to market signals, they often lack governance and performance validation that results in low forecast accuracy, and forecasting becomes a source of recurring operational tensions rather than decision support.

Business Issue

The major problem ABC Company faces is the low accuracy and unpredictability of its sales forecast, which has averaged around 72% over the past two years. This inaccuracy severely impacts operations. When the forecast is too low, the company suffers from high prices for both vessels and the raw materials due to sudden, urgent bookings. Conversely, an overly high forecast forces ABC Company to pay cancellation fees for booked vessels and finished goods. This combination of raw material uncertainty, price volatility, logistical problems, and low sales in 2023 creates a highly problematic situation for ABC Company. These factors cascade into numerous operational problems across the procurement, production planning, sales planning, shipping, and after-sales processes with customers. Within this context, the Sales

Operations Department holds a crucial role, as its sales forecast determines all subsequent operational processes—from procurement and production planning to vessel booking. Consequently, significant pressure is placed on the Sales Operations Department to generate a highly accurate sales forecast. Achieving this accuracy is essential for ensuring efficient operations and, ultimately, securing sustainable long-term profitability for the company.

Research Questions and Research Objectives

The primary objective of this research is to increase the sales forecast accuracy at ABC Company by addressing the root causes of the current inaccuracies and determining the most effective forecasting method for the company. To guide the research process, the study is structured around three key questions: identifying the major factors affecting forecast accuracy, developing solutions to solve and prevent these root causes, and determining the optimal forecasting technique for ABC Company. To ensure data accuracy and focus, the scope of the research is limited to the monthly sales data and performance of ABC Company's Product sales from July 2023 to June 2025. A key limitation is the reliance on the company's internal data, which may not be fully applicable to other organizations, and the constraint of a dataset spanning less than two years during a period of high market volatility.

Research Scope and Limitation

This research will be presented across five chapters. Chapter I introduces the research background, covering the FMCG industry, company profile, business issues, and research objectives. Chapter II reviews relevant literature on forecasting techniques, factors impacting accuracy, and presents a conceptual framework. Chapter III details the research methodology, including approaches, assumptions, and data collection methods. Chapter IV provides the data analysis using the DMAIC methodology to identify root causes and propose forecasting solutions. Finally, Chapter V concludes the research by answering the established questions, verifying if objectives were met, and offering recommendations for implementation and future studies.

LITERATURE REVIEW

1. Theoretical Foundation

1.1.Lean

Lean Six Sigma is a well-established technique widely used in industry for continuous problem-solving through a systematic approach. According to Wang et al. (2016), numerous companies have embraced Six Sigma projects over the past three decades to improve competitiveness. It emerged from integrating two quality management philosophies: Lean and Six Sigma. Lean, originating from the Toyota Production System, emphasizes waste elimination and value creation from the customer's perspective, fostering the identification and solution of problems (Womack et al., 1991). Its successful implementation is guided by a continuous framework of five principles (Womack and Jones, 2013): specifying value from the customer's view; identifying the value stream to pinpoint value-adding and non-value-adding steps; creating continuous flow to shorten cycle times; establishing a pull system for customer responsiveness; and seeking perfection through ongoing analysis to increase value and eliminate waste.

A common Lean toolset is the 5S framework, aimed at reducing waste, improving consistency, and enhancing productivity (Bicheno & Holweg, 2009). Successful implementation requires committed top management to drive the program and secure employee buy-in (Carreira, 2004). The original Japanese 5S—Seiri, Seiton, Seiso, Seiketsu, and Shitsuki—are commonly translated as Sort, Set in order, Shine, Standardize, and Sustain (Bicheno & Holweg, 2009). Sort involves discarding unneeded items and organizing necessary ones by frequency of use. Set in order entails placing items ergonomically with visual management tools like shadow boards. Shine means keeping the work area tidy for easy anomaly detection. Standardize requires establishing simple, reliable standards for the first three steps. Sustain involves making these practices a habit through regular audits and continuous commitment. The typical improvement cycle used in Lean is the Plan-Do-Check-Act (PDCA) cycle (Bicheno & Holweg, 2009).

This cycle begins with planning and creating a hypothesis based on customer needs. The "Do" stage involves implementing the planned improvement. Next, the "Check" stage verifies if the implementation was correct and yielded expected results. Finally, the "Act" stage involves making necessary adjustments, creating standards, and planning further improvements based on the findings. As the cycle repeats, the end result is continuously enhanced.

1.2. Six Sigma

While Lean is focused on eliminating waste and creating efficient flow, Six Sigma on the other hand, are used to improve the product's performance and product's quality (Mwacharo, 2013; Madsen et al., 2017). Six Sigma has at least four streams of thought (Tjahono et al., 2015). The first stream defines Six Sigma as a statistical tools to enhance the quality management to construct a process improvement (Goh and Xie, 2004). The main purpose is to improve the Six Sigma of the performance to the level that fulfil the cutomer requirements referred as the Critical To Quality (CTQ). The second stream of thoughts defines Six Sigma as a operational philosophy of management, not only limited to manufacturing but also applicable to the whole supply chain (Chakrabarty and Tan, 2007). The third stream defines Six Sigma as a business culture, they argue that the success of Six Sigma isn't only define by the statistical tools, but also the commitment from the top management to implement it (Markarian, 2004). The fourth stream define Six Sigma as a well structured analysis methodology that focuses on reducing process variability and removing waste (Banuelas and Antony, 2004).

By combining these approaches, Lean Six Sigma aims to achieve both speed and precision in processes, making it a widely adopted strategy in diverse industries (Kurnia & Purba, 2021). The key principles underpinning LSS include defining value from the customer's perspective, mapping value streams, eliminating non-value-added activities, and fostering a culture of continuous improvement (Costa et al., 2020). While its benefits—such as improved quality, reduced cost, and enhanced customer satisfaction—are well documented, researchers also highlight common challenges such as cultural resistance, lack of leadership support, and inadequate training (Albliwi et al., 2014).

1.3. Lean Six Sigma and DMAIC

Combining Lean and Six Sigma creates a data-driven, top-down business strategy to improve a company's productivity and product quality (Singh and Rathi, 2019). As noted by Pepper and Spedding (2010), implementing Lean without Six Sigma wastes potential, while implementing Six Sigma without Lean results in a mere statistical tool lacking a framework for systemic improvement. Lean Six Sigma aims not only to enhance financial results through production process improvements but also to help organizations build adequate relationships with society, employees, and the environment (Galdino de Freitas and Gomes Costa, 2017). This integration enables companies to form a powerful system for solving problems more effectively (Antony et al., 2017). Its implementation generally follows one of two methods: the Define-Measure-Analyze-Improve-Control (DMAIC) framework for improving existing processes (Ricciardi et al., 2020) or the Define-Measure-Analyze-Design-Verify (DMADV) framework for developing new designs or products (Vincent, 2002; Uluskan and Oda, 2019).

This paper focuses on implementing Lean Six Sigma via the DMAIC methodology to improve sales forecasting at ABC Company. Each phase serves a distinct purpose supported by structured tools. The Define phase establishes project scope, objectives, and customer requirements using tools like SIPOC diagrams and Voice of Customer analysis. The Measure phase develops baseline performance metrics and validates measurement systems through process mapping and capability analysis. This phase also set the Critical to Quality (CTQ) measures that quantifies the performance metrics, which is the accuracy of the forecast. The Analyze phase identifies root causes of variation using tools such as Ishikawa fishbone diagram and hypothesis testing. The Improve phase generates and implements solutions via methods like Design of Experiments and Kaizen events. Finally, the Control phase sustains improvements using control charts, standard operating procedures, and visual management systems (Uluskan, 2016). Although Lean Six Sigma originated in manufacturing, it is now applicable in non-manufacturing environments as well

(Singh and Rathi, 2019). Its broad applicability extends to services, healthcare, government, non-profits, education (Antony et al., 2017), as well as automotive, textile, steel, and aerospace industries (Sordan et al., 2020). It is a well-established process excellence methodology across almost every sector, regardless of size or nature (Gijo et al., 2019), and is useful for both small-and-medium-sized and large organizations (Antony et al., 2017). This widespread adoption demonstrates its role as one of the best strategies for organizational excellence (Sreedharan and Raju, 2016). However, it is important to remember that achieving maximum strategic and management efficiency cannot be based merely on replicating Lean principles and models.

1.4. Forecasting Techniques

Understanding Lean Six Sigma provides a strategic framework for ABC Company to identify the root causes of its inaccurate sales forecasts. However, achieving sustainable operations requires more than just solving these root causes; the company must also develop a robust and reliable forecasting method. One applicable technique is Holt-Winters exponential smoothing, a classical time-series method designed to model patterns influenced by level, trend, and seasonality. Research by Narayana and Handayati (2023) demonstrated that the Holt-Winters method can improve forecast accuracy by up to 10%. Unlike simpler methods like moving averages, this model does not assume stationary demand but decomposes a time series into structured components, enabling it to capture systematic changes over time (Holt, 1957; Winters, 1960).

This method is widely used in operations and supply chain management, particularly where demand follows recurring seasonal cycles and gradual trends (Gardner, 2006; Hyndman et al., 2008). For demand with relatively constant seasonal fluctuations, the additive Holt-Winters model is applied using a system of equations that update the level, trend, and seasonal components with respective smoothing parameters (α, β, γ). The model remains relevant for several reasons: empirical evidence shows it consistently outperforms naïve and moving average methods in seasonal environments (Makridakis et al., 1998; Gardner, 2006; Narayana & Handayati, 2023); it offers high transparency and managerial interpretability as each component can be examined; and it can operate effectively with limited historical data, which suits ABC Company's situation (Syntetos et al., 2009).

Level Update	$L_t = \alpha(Y_t - S_{t-m}) + (1-\alpha)(L_{t-1} + T_{t-1})$
Trend Update	$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1}$
Seasonal Update	$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-m}$
Forecast Equation	$Y_{t+h} = L_t + hT_t + S_{t+h-mk}$

Where:

$Y_{t+h} = Forecasted\ demand$
$Y_t = Actual\ Demand$
$\alpha, \beta, \gamma = Smoothing\ Parameter$
$L_t = Level, representing\ baseline\ demand$
$T_t = Trend, representing\ direction\ and\ rate\ of\ change$
$S_t = Seasonal, representing\ cyclical\ effect$

Despite its advantages, Holt-Winters exponential smoothing assumes linear trends and stable seasonal patterns, meaning its performance can deteriorate during abrupt changes or irregular demand spikes. Such limitations can be mitigated later by integrating machine learning-based models once forecast governance and feasibility integration are established (Gardner, 2006; Hyndman et al., 2008). In this research, Holt-Winters is employed as a quantitative baseline model to assess how trend and seasonality affect demand, and its performance will be compared against ABC Company's current forecasting method.

2. Theoretical Foundation

2.1. Lean Six Sigma in manufacturing & services industries

Lean Six Sigma (LSS) has been extensively applied across industries to improve operational efficiency, reduce defects, and enhance customer satisfaction. In the manufacturing sector, the adoption of LSS has yielded significant reductions in cycle times and production costs. Tjahjono et al. (2015) reviewed over 200 studies and found that LSS projects commonly deliver defect reduction of up to 70% and productivity gains exceeding 40%, especially in high-volume production environments. These benefits stem from the systematic nature of the DMAIC methodology, which enforces rigorous problem identification and root cause elimination. Daniyan et al. (2022) also prove that the application of LSS in the manufacturing of railcar's bogie assembly process is successful. The results showed significant improvement in the process cycle efficiency which improved by 46.8%, the reduction of lead time by 27.9%, 59.3% increase in the value added time, and 71.9% reduction of the non-value added time after the implementation of LSS.

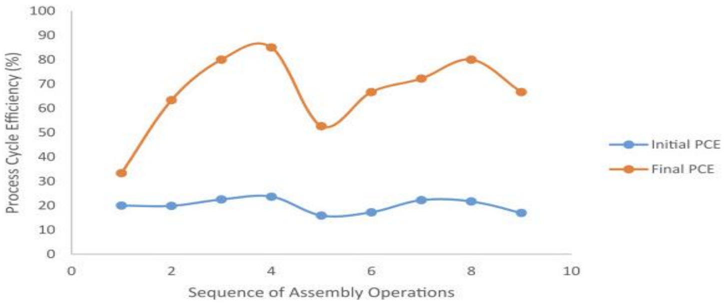

Figure 1. Process Cycle Efficiency Improvement (Daniyan et al., 2022)

In service sectors, such as healthcare and banking, LSS has proven effective in streamlining administrative processes and reducing non-value-added activities. For example, Laureani and Antony (2017) highlight successful healthcare applications where patient waiting times were reduced by 30–40% through DMAIC-driven improvements. These cases demonstrate the versatility of LSS beyond its manufacturing roots. On top of that, Mitchel et al. (2025) also proven to be able to improve operating room first case on-time performance from 39% to 79% twelve months after the improvement was implemented, and this improvement also reduce delay by approximately 49% during the project.

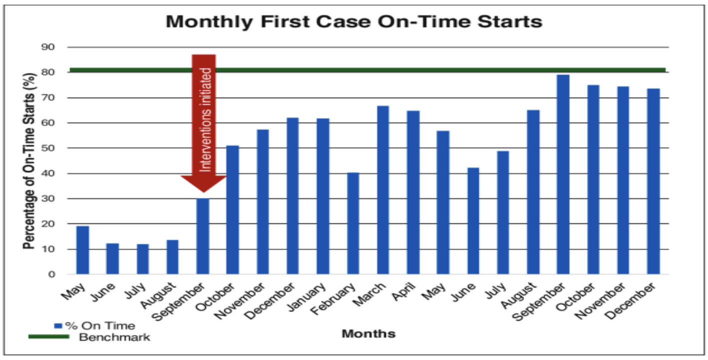

Figure 2. Monthly First Case On-Time Starts (Mitchel et al., 2025)

2.2. Lean Six Sigma in Food and Beverage Industries

The food and beverage (F&B) industry presents unique operational challenges due to stringent quality requirements, perishable raw materials, and strict food safety regulations. Research indicates that Lean Six Sigma, when properly adapted, can deliver substantial performance improvements in this sector. A systematic literature review by Costa et al. (2020) on Lean Six Sigma in the food industry revealed that projects in F&B companies often target waste reduction, particularly in raw material handling and packaging. Common DMAIC tools applied include SIPOC diagrams for process mapping, Pareto analysis for defect prioritization, and FMEA for risk assessment, with reported average improvements including defect reductions of 25–50%, enhanced compliance, and reduced processing time. Two specific case studies illustrate its effective implementation. The first involved an Indian dairy company that used the DMAIC approach to reduce packaging defects in milk sachets. The team identified sealing temperature variation as the root cause and addressed it by standardizing equipment settings and introducing real-time monitoring. This intervention successfully lowered defect rates from 8% to less than 1%, yielding significant cost savings and improved product safety (Singh & Singh, 2020). The second case was at a beverage bottling plant, where a major soft drink manufacturer applied DMAIC to tackle high carbonation defects in bottled products. The Analyze phase identified machine vibration during filling as a key contributor. Subsequently, process stabilization and preventive maintenance measures implemented in the Improve phase reduced defect incidence by 70%, thereby enhancing both product quality and customer satisfaction (Antony et al., 2019).

2.3. Lean Six Sigma in Forecasting

Applying Lean Six Sigma to forecasting involves treating forecast creation as a process with defined customers (e.g., Sales Operations, supply chain, finance), critical-to-quality characteristics (CTQs) like Mean Absolute Percentage Error (MAPE) and bias, waste sources such as manual rework, and special-cause variation from events like promotions. The goal of this research is to reduce forecast error and bias, stabilize the process, and institutionalize controls, not to advocate for a single algorithm, as achieving 100% forecast accuracy is widely considered impossible (Liao and Chang, 2010). In practice, the DMAIC framework typically wraps around the forecasting system, with the "Improve" phase potentially introducing or tuning statistical models (e.g., Holt-Winters, ARIMA) and redesigning processes. Evaluating forecast performance requires multiple complementary metrics. MAPE assesses relative error for interpretability across periods (Hyndman and Athanasopoulos, 2021), while the Root Mean Square Error (RMSE) captures the magnitude of error, which is critical for operations (Hewamalage et al., 2022; Hyndman & Koehler, 2006). Forecast bias must also be evaluated to identify systematic over- or under-forecasting tendencies, which is essential for avoiding persistent planning mismatches (Miah et al., 2018; Rakićević, 2015).

Several studies demonstrate this application. A university-backed study on a multi-store bakery chain used DMAIC to redesign demand forecasting and distribution (Bazan et al., 2023). The team defined CTQs, mapped processes, cleaned data, and segmented SKUs by demand patterns. In the Improve phase, they deployed a seasonality-aware model (finding ARIMA superior to Holt-Winters) and synchronized replenishment, followed by a Control plan with dashboards. Another study in the beverage industry used time-series forecasting to identify peak periods and implemented Lean Six Sigma/Leagile countermeasures to improve service efficiency and reduce costs. The DMAIC process captured KPIs, isolated peak drivers, synchronized production and staffing to forecasts, and maintained controls, resulting in more demand-shaped operations. In Indonesia, Narayana and Handayati (2023) applied DMAIC for demand forecasting at a lubricant company. After analysis, they selected Holt-Winters to handle seasonality and trend, implemented governance controls, and achieved a 10% error reduction with significant cost savings, further proving the methodology's effectiveness. Although substantial evidence proves Lean Six Sigma's effectiveness in improving business processes, most case studies are from manufacturing or healthcare, with a relative lack of evidence from the Food and Beverage (F&B) industry. This study aims to fill that gap by implementing Lean Six Sigma to improve the sales forecast for finished goods at ABC Company.

2.3. Integrating Expert Opinion

While creating accurate data analysis helps a company better predict sales demand, relying solely on data does not fully utilize all competitive advantages. For ABC Company, a key strength lies in its long-standing production experience and customer relationships. Incorporating expert advice into quantitative forecasts—known as integrated forecasting methods—can build a stronger foundation for forecast creation when done systematically (Arvan, 2019). This approach requires that advisors are professionals with relevant field expertise, and their judgment, combined with management's Sales Operations know-how, enhances forecast quality. Since ABC Company's sales forecast uses a weekly timeframe, the application of expert opinion must be specific and timely. Additionally, the level of expertise must be weighted, meaning not all advice carries equal influence, as outlined in Expert Knowledge Elicitation (EKE) principles (Önkal, 2017). Research supports that integrating quantitative forecasts with human judgment improves sales forecast accuracy, particularly in accounting for seasonality, because purely quantitative methods often fail to predict extreme increases or decreases during peak or low seasons. For instance, an interview study with thirty-two top-level managers in B2B companies revealed that combining sales managers' capabilities with AI utilization significantly enhances company sales (Hautamäki, 2025). Therefore, ABC Company can improve its forecasts by systematically combining the judgment of industry experts focused on short-term demand analysis with the customer expertise and know-how of its sales managers.

METHOD

This research aims to develop a more accurate and reliable sales forecasting method for ABC Company through a mixed-method, case study approach. It integrates quantitative forecasting models with qualitative expert judgment from sales managers and industry professionals to create a robust, practical forecasting framework. The study is applied, descriptive, and focuses specifically on ABC Company's context.

Research Design

This research will utilize the DMAIC methodology as its framework. The Define Phase initiates the process by identifying the core problem of inaccurate finished goods sales forecasts, which lead to planning inefficiencies and increased costs. It defines Critical-to-Quality (CTQ) characteristics such as forecast accuracy percentage which quantifies into Mean Absolute Percentage Error (MAPE), Forecast Bias, and Root Mean Square Error (RMSE) as the main parameters. Key stakeholders, including the sales, Sales Operations, shipping departments, and production planners, are engaged to set project objectives. The scope focuses exclusively on the accuracy of ABC Company's sales forecasting for finished goods, intentionally neglecting external factors like raw material price and availability under the assumption that the company will procure raw materials at any market price. Following definition, the Measure Phase involves collecting the current forecast and actual sales to analyze the relationship between customer demand, manufacturing, and delivery. This phase measures current forecasting performance using historical sales, forecast data, and error metrics like MAPE and RMSE to establish a performance baseline that quantifies the gap between actual and forecasted demand.

The Analyze Phase assesses the fulfillment ratio to determine forecast accuracy and investigates the root causes of unshipped quantities using tools like fishbone diagrams. Historical factors at ABC Company, such as seasonal fluctuations or vessel availability, are examined. Supporting this, a study by Antony et al. (2019) in beverage bottling identified poor Sales Operations planning (S&O) integration as a major factor affecting forecast reliability. Subsequently, the Improve Phase focuses on developing and implementing solutions to address these root causes. This includes technical improvements, refining forecasting techniques like ARIMA or Holt-Winters to better capture market seasonality, and process standardization guided by Lean and Six Sigma principles. As benchmarking studies by Bazan et al. (2023), Narayana & Handayati (2023), and Barbosa et al. (2025) indicate, no single forecasting method fits all; therefore, multiple methods must be tested and integrated with expert judgment to find the best fit for ABC Company. Finally, the Control Phase establishes mechanisms to sustain improvements, such as accuracy dashboards, control charts, and periodic review meetings, creating a feedback loop for continuous monitoring. This approach aligns with findings by Karthi et al. (2011) in the food packaging sector, where standardized review cycles significantly reduced process variability over time.

Data Collection Method

This research will be using the combination of quantitative and qualitative data to enhance the accuracy of ABC Company's forecast moving forward and maximize their competitive advantage against the other competitor in this field. One of the main advantages of ABC Company is their long-standing production and relationship with many experts from inside and outside the organizations; incorporating their judgment will enhance the accuracy of their forecast (Abolghasemi, 2020). Their advices, combined with the Sales Operations know-how of the company's management, would create a strong foundation for the forecast creation if used in a systematic way (Arvan, 2019). An interview with thirty-two top-level managers in B2B companies showed that the combination of sales manager capability and the utilization of AI improves the sales of the company (Hautamäki, 2025).

Data Period, Unit of Analysis, and Data Structure

The analysis in this research uses monthly time-series data from January 2024 to December 2025. This time-series was chosen to align with the company's planning timeframe and management point of view for their monthly reviews. The unit of analysis is finished goods sales volume (metric tons) to all ABC Company's customer. To measure the forecast performance, Call-Off will be treated as the sales forecast (F_t) and the actual sales is treated as realized output (A_t). Forecast error will be calculated using metrics such as MAPE, Forecast Bias, and RMSE to establish a baseline performance and monitor the improvement.

Data Analysis

The research methodology encompasses four phases aligned with the DMAIC structure. In the Define phase, foundational elements are established, including a project charter and a SIPOC diagram to outline stakeholders in the forecasting process. Key data sets such as forward sales, historical sales, production, and shipping information are also gathered during this initial stage (Guo, 2021). Subsequently, the Measure phase utilizes the collected data to evaluate the current forecasting performance. This evaluation employs specific metrics: Mean Absolute Percentage Error (MAPE), Bias, and Root Mean Square Error (RMSE). The primary objective of this phase is to establish a baseline and identify the existing variability in the accuracy of sales forecasts. The analysis then progresses to the Analyze phase, which focuses on diagnosing the sources of forecast inaccuracy. This begins with identifying contributors to forecast errors and applying Pareto analysis to select the most significant ones. A fishbone diagram is subsequently used to trace the root causes of these top contributors, categorizing them across people, processes, technology, and external factors. These root causes are rigorously evaluated to confirm their direct relationship to the observed forecast errors.

Finally, the Improve phase involves a structured approach to developing solutions. First, all identified root causes are reviewed and prioritized using an impact-effort matrix (Samuel, 2020). Improvements are then pursued in two key areas: addressing technical root causes with solutions designed for both resolution and future prevention, and enhancing overall forecast accuracy through a combined quantitative and qualitative analysis. The quantitative analysis employs the Holt-Winters method, chosen for its effectiveness with seasonal data characteristic of the industry (Guo, 2021). The Holt-Winters forecast is validated using MAPE and sensitivity testing, where a lower MAPE results in a higher α (representing trust in the model forecast), indicating greater reliability. The qualitative analysis integrates expert judgment by weighting opinions via the EKE method (Önkal et al., 2016). Expert weight is determined through an evaluation matrix based on experience, knowledge, and confidence, with scores normalized and integrated into the final forecast.

Table 1. Example of Expert Opinion Weighing

Expert	Experience	Knowledge	Confidence	Total Score	Normalized Score
A	3 (High)	3 (High)	3 (High)	9	0.5
B	1 (Low)	1 (Low)	1 (Low)	3	0.17
C	2 (Med)	2 (Med)	2 (Med)	6	0.33

The last step in this phase is to combine the qualitative and the quantitative data, this is crucial step that transforms two distinct streams of insight (model-driven forecasts and expert judgement) into one cohesive final forecast. This forecast integration or judgmental–quantitative combination forecasting data analyzing is to integrate both the quantitative data and qualitative data. First, we'll get the weighted forecast from the experts as shown in the table below.

Table 2, Example of Expert's Forecast Weighing

Expert	Expert's Weight	Expert's Forecast (Ton)	Weighted Forecast (Ton)
A	0.5	150	75
B	0.17	160	27.2
C	0.33	140	46.2
Total			**148.4**

After getting the weighted forecast from the experts, we'll integrate the the weighted experts opinion into the quantitative forecast using the formula below (Makridakis, 1997) :

$$Final\ Forecast\ = (\ \alpha * Model\ Forecast) + ((1-\alpha) * Expert\ Forecast)$$
$$Model\ Forecast = Output\ from\ Holt - Winters$$
$$Expert\ Forecast = Weighted\ aggregate\ \text{of}\ expert\ elicitation$$
$$\alpha = Trust\ in\ the\ model, adjusted\ based\ on\ data\ confidence$$

To provide an illustration, here is an example calculation with several assumptions as follows:
1. The MAPE results is at 15%
2. The α used in the calculation is 0.4
3. The forecasted sales is only one period at 170 tons.

$$Final\ Forecast = (\ \alpha * Model\ Forecast) + ((1-\alpha) * Expert\ Forecast)$$
$$Final\ Forecast = (0.4\ * 170) + ((1-0.4) * 148.4)$$
$$Final\ Forecast = \ 157.4\ Tons$$

From the simulation of the calculation, we could see that the expert opinion has a higher influence, as the confidence in the model is relatively low, (= 0.4). This simulation will give ABC Company a more reliable sales forecast moving forward, as it integrated both the expert judgment and the simulation based on historical data in which already accounted for the seasonality and the residual errors in the simulation method. In the control phase, the focus is to create a reliable, repeatable, and consistent process so this research can improve ABC Company's business sustainability. The first step is to create a clear KPIs for the forecast accuracy, and create accuracy dashboards to monitor the forecast accuracy overtime. The second step is to establish a control board, this is needed to ensure that the improvement for technical issues are implemented consistently, and those issues won't be repeated in the future. The last step is to create a periodic review that includes all the stakeholder involved in this process, from the sales team, Sales Operations team, production team, and the shipping team.

RESULTS AND DISCUSSION

This chapter presents the analysis and findings of a study applying the Lean Six Sigma DMAIC framework to diagnose and improve sales forecasting at ABC Company, where reliable forecasting is critical for efficient operational process.

1. Define Phase

This study will use the combination of quantitative and qualitative data from ABC Company from January 2024 until December 2025. The qualitative data will be collected from the interview with the key persons in ABC Company which will be the primary data for this study. The quantitative data will be the secondary data that consist of the forecast and actual sales data gathered from the company internal operational data, with forecast accuracy quantitatively measured using Mean Absolute Percentage Error (MAPE), Forecast Bias, and Root Mean Squared Error (RMSE).

2. Measure Phase - Baseline Forecast Performance

The primary objective of this phase is to quantify the baseline performance, referred to as the "before condition," to determine the stability of the current forecasting signal, thereby establishing a reference point for evaluating the effectiveness of subsequent improvements. This quantification involves measuring the baseline accuracy performance against critical-to-quality (CTQ) metrics, identifying whether the forecast error is stable and predictable or highly variable over time, determining if forecast deviations are random or exhibit a consistent directional bias, and providing quantitative evidence to justify a deeper analysis into the root causes of inaccuracies.

2.1. Baseline Trend and Variability Analysis

Based on interviews with key personnel from Sales, Sales Operations, PPIC, and Shipping, the current forecasting process primarily relies on customer call-off data and team intuition as demand signals, conducted on a weekly or monthly basis without a formal cut-off period, though an informal mid-month cut-off implemented in Q2 2025 slightly improved accuracy despite ongoing adjustments due to revised customer instructions. The baseline performance, measured by comparing monthly call-off forecasts to actual sales from January 2024 to December 2025, reveals a significantly inaccurate and unstable forecasting signal with a consistent over-planning bias, as evidenced by a MAPE of 56.52%, a Forecast Bias of +47.97%, and an RMSE of 50% of actual sales volume This consistently positive bias indicates a systematic over-forecasting behavior rather than random deviation, while the high RMSE value signifies substantial operational exposure during periods of large forecast errors.

2.2. Forecast vs Actual Trend Interpretation

In general, ABC Company’s call-off follows the overall sales movement, showing that the demand signal captures some of the business trends. However, the deviation from the call-off varies substantially over time. Several periods display larget deviations, particularly from May to November 2024 which shows that the current forecast is not reliable and tend to have high volatility in terms of accuracy.

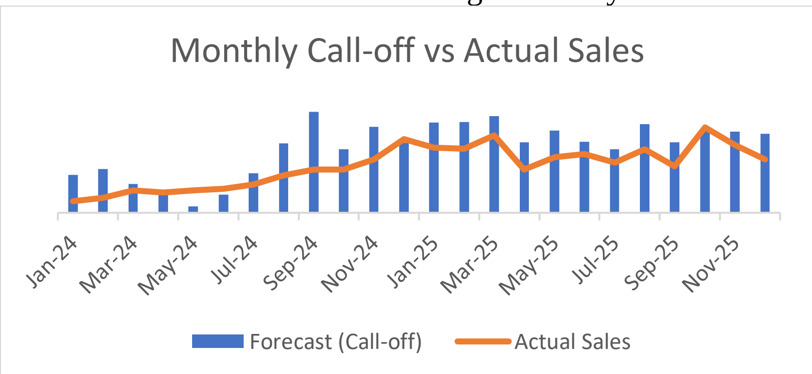

Figure 3. Monthly Forecast (Call-off) vs Actual Sales

2.3. Forecast Error Stability and Variation

To evaluate the stability and reliability of the forecast, monthly error variation was examined. High variation will indicates unstable processes which needs to be clarified whether the variation is driven by common cause or specific cause. To evaluate this, monthly error pattern is visualized using APE% charts as shown below.

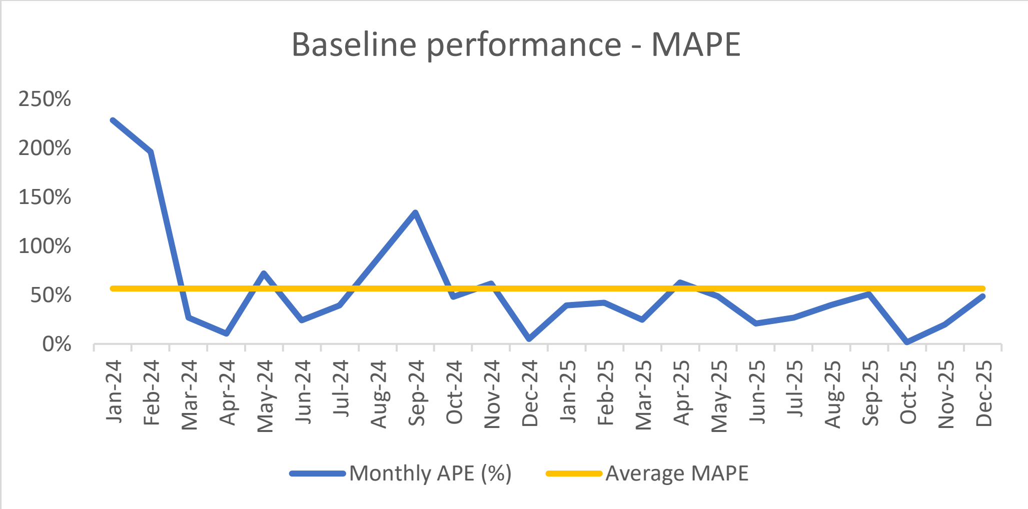

Figure 4. Baseline Performance – Monthly APE%

Figure 6. shows that monthly APE% values fluctuate significantly across the research period. This indicates that forecast accuracy is not stable, especially during 2024. This suggests that the forecasting process may contain common-cause variation (external market fluctuation) and specific-cause variation (major reschedule, supply chain constraints). Along the way, there is a progress in the APE%, where nearing the end of research period the APE% is getting lower even though it still indicates instability. This shows the importance of conducting a thorough analysis to determine what factors drive high-variance in the forecast.

2.4. Interpretation of Forecast Bias and Directional Deviation

Forecast bias is another critical baseline finding in this research. In ABC Company's case, the forecast bias is strongly positive (+47.97%) which indicates the possibility of systematic over-forecasting relative to the actual sales as shown in Figure 5.

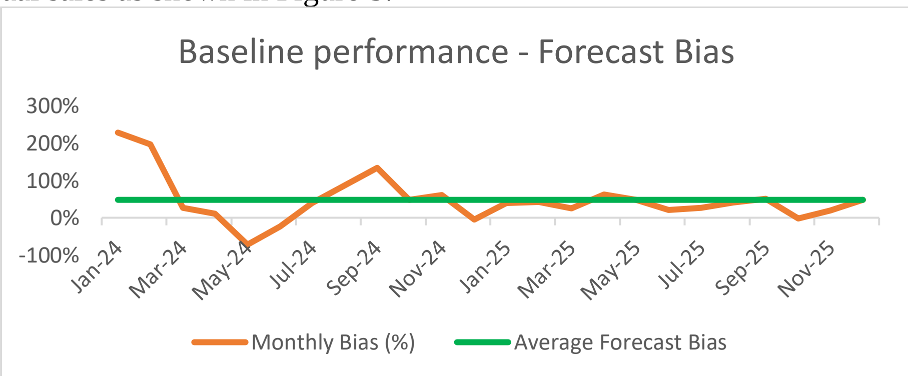

Figure 5. Baseline Performance – Forecast Bias

From an operational perspective at ABC Company, persistent over-forecasting creates significant inefficiencies. Firstly, it leads to inflated procurement, signaling a higher volume requirement upstream and causing excess imports of raw materials months in advance. Secondly, it generates production uncertainty, resulting in unstable schedules, frequent adjustments, and the overproduction of finished goods. Additionally, the high volume forecasts cause vessel booking volatility, compelling the shipping team to overbook vessels and create excessive contracts with shipping liners, incurring extra costs and operational inefficiency. This systematic bias also necessitates frequent replanning cycles and prolongs coordination meetings across Sales, Logistics, PPIC, and Warehouse teams.

2.5. Interpretaion of RMSE and Operational Exposure

Previously, MAPE provides a percentage-based measure of forecast accuracy. This time, RMSE provides the magnitude of forecast deviation in absolute tonnage and emphasizes the presence of large deviation periods. The RMSE values which accounts for 50% of the monthly sales volume, indicates that the average forecast deviation is very significant. Large forecast deviation in ABC Company already translated into major exposure, such as overcapacity of both the raw material and finished goods, frequent changes in shipment planning, and also lack of deliverable goods at some moments. Therefore, this shows that the inaccuracy of ABC Company’s forecast not only frequent, but potentially severe in the operational and financial terms, especially because the raw materials is a highly volatile commodity in the last several years.

2.6. Summary of Measure Phase Findings

The baseline measurement confirms that forecasting performance at ABC Company is unstable, directionally biased, and exhibits substantial planning deviation, as demonstrated by a high average deviation (MAPE of 56.52%), a systematic over-forecasting behavior (Bias of +47.97%), and a large deviation magnitude (RMSE of 50% of monthly sales). These findings provide strong quantitative evidence that the current forecasting is unreliable for stable supply chain planning, necessitating improvements not only in forecasting techniques but also in governance, cross-functional alignment, and the structured management of the forecast. With the baseline performance established and the forecasting error confirmed as substantial, the subsequent step involves a deeper analysis focused on identifying root causes to ensure that subsequent improvements are both effective and efficient.

3. Analyze Phase

The analysis phase, initiated after confirming the forecasting performance at ABC Company as inaccurate (MAPE 56.52%), systematically biased (Bias +47.97%), and exposed to large deviations (RMSE of 50% of monthly sales), aims to determine the systemic causes behind these substantial gaps. This phase is guided by two key principles: first, that forecast accuracy depends not just on prediction but on the stability and governance of the signal driving planning; and second, that forecast errors can also stem from execution distortion, where existing demand cannot be fulfilled due to feasibility constraints like production capacity or vessel availability, leading to shipment delays. To structure this systemic analysis, a fishbone diagram (Ishikawa) supported by cross-functional interviews with Sales, Sales Operations, Logistics, and PPIC is employed. The interview coding sheets reveal consistent alignment across functions on several core issues: the operational forecast for production and shipping is based on customer call-off data rather than firm contracts; there is a shared acknowledgment of a persistent over-forecasting tendency; repeated identification of customer-requested delays and production capacity constraints as top deviation drivers; and the recognition that while a forecast governance rule exists (a mid-month cut-off), it is frequently undermined by late changes in the subsequent periods.

3.1. Interview-Based Analysis of Forecasting Misalignment

A fundamental misalignment emerges from the universal reliance on customer call-off as the primary forecast signal. The Sales and Shipping teams interpret call-off as a firm commitment to meet customer-required dates, whereas the PPIC function views it as a tentative planning signal subject to production constraints. This differing interpretation creates a structural tension, leading to frequent mismatches between planned and shipped volumes. Furthermore, a critical demand-supply feasibility mismatch arises from production sequencing constraints. Even with sufficient total capacity, the production line can only run several SKUs at a time. This indicates that forecast deviations are not merely due to poor demand estimation but stem from a forecast that does not incorporate critical execution constraints at the time of confirmation, explaining the persistent positive bias where forecasted volumes consistently exceed realized sales. Compounding these issues is a significant problem with forecast governance. While a formal cut-off date exists, it is not uniformly enforced, with post-deadline call-off changes frequently justified for Sales reasons. PPIC, however, cannot flexibly accommodate these late additions due to fixed production schedules. This creates a dilemma: accommodating changes strengthens customer relationships at the expense of disrupting production for other orders, while rejecting them risks losing sales. From a forecasting perspective, this lax governance converts timing uncertainty into forecast error, inflating metrics like MAPE even when total demand is eventually met. The interview analysis conclusively shows that forecast inaccuracy at ABC Company is systemic, rooted in three core issues: misaligned functional interpretations of the forecast signal, significant feasibility constraints in production and logistics, and the existence of governance mechanisms that lack consistent enforcement. This reveals that the deviation originates not from simple forecasting error but from operational misalignment and weak process discipline, allowing volatility to persist throughout the planning and execution cycle.

3.2. Fishbone Analysis of Forecast Deviation

The forecasting issues are comprehensively structured using a Fishbone (Ishikawa) Diagram, categorized into six key areas. The 'Man' category identifies a core misalignment in how different functions interpret the forecast signal: Sales and Shipping teams treat customer call-off as a firm commitment, while PPIC views it as provisional. This lack of shared understanding, combined with an absence of accountability for forecast inaccuracy, reinforces an over-forecasting tendency and creates internal mistrust, directly contributing to a persistent positive forecast bias and increased MAPE. Under 'Method (Process and Governance)', a major instability driver is the lack of enforced discipline. Although a monthly call-off cut-off exists, it is frequently overridden by Sales teams accommodating late customer changes without a structured exception process. This weak governance, coupled with a short forecasting cadence that misaligns with long procurement lead times, forces PPIC into speculative planning, increasing forecast volatility and the gap between planned and realized volumes. The 'Machine (System and Tools)' category highlights significant systemic weaknesses. The over-reliance on error-prone manual spreadsheets for forecasting, combined with a lack of formal change control or approval for data alterations, creates inconsistency and high risk. This reactive system means forecast deviations are only detected after execution failures occur, such as stock shortages or missed shipments, rather than being prevented. The 'Material (Production and Feasibility)' branch is identified as the most dominant root cause. Persistent operational constraints, including production capacity limitations and inflexible SKU sequencing create a fundamental mismatch between forecasted demand and executable supply. With the factory operating near full capacity, any delay in one SKU cascades, compounding forecast errors over time and directly causing shipment deviations. Finally, 'Mother Nature (Environment)' encompasses critical external factors. The primary contributor is frequent customer requests for order delays or expedites, often accommodated based on Sales judgment, which results in excess stock. Furthermore, seasonal vessel unavailability during peak periods, combined with production timing mismatches, exacerbates shipment delays and the deviation of actual sales from the forecast, further inflating error metrics.

3.3. Analyze Phase Summary

The analyze phase concludes that improving forecast accuracy at ABC Company cannot be achieved merely by implementing a new forecasting algorithm; it requires a systemic redesign of the forecasting process and its governance. Key improvements must address the fundamental misalignment in how the call-off signal is interpreted and committed to across functions, explicitly incorporate critical feasibility constraints such as production sequencing and capacity into the forecast, strengthen the discipline around the cut-off deadline with a structured exception-handling mechanism, and enhance operational visibility through consistent performance tracking.

4. Improve Phase

The analyze phase reveals that forecast inaccuracy is systemic, stemming from weak governance, demand-supply feasibility mismatches, and execution-related timing distortions, rather than just a limitation of forecasting techniques, as evidenced by the consistent positive bias and large deviations that indicate the process frequently over-promises unattainable volumes. Consequently, this phase aims to redesign ABC Company's forecasting system into a stable, executable, and decision-oriented framework to reduce forecast error, improve operational reliability, and enhance brand image. Guided by the principles of prioritizing stability over optimization and executability over sophistication, the improvements are structured into four sequential streams: forecast governance stabilization, feasibility-integrated planning, quantitative forecast improvement, and the integration of expert judgment, ensuring each enhancement is built upon a stable and executable foundation.

4.1. First Stream - Development of Forecast Governance Stabilization

The primary objective of the first improvement stream is to establish forecast stability, which is foundational for reliable production and shipment planning. Without a stable forecast, production schedules are highly likely to miss shipment deadlines, causing cascading delays across multiple SKUs. Analysis indicates that weak governance and a planning process solely responsive to customer requests—without incorporating production feasibility—are key sources of volatility, creating a "moving target" for production teams that inflates forecast error metrics like MAPE. To address this, the research proposes a new three-core-forecast governance framework. First, a Two-Tier Forecast Structure is introduced, comprising a Fixed Forecast (FF) locked after the monthly cut-off for binding production and logistics planning, and a non-binding Flexible Outlook (FO) for visibility beyond the freeze window. Second, a formal Forecast Exception Management process is established, requiring cross-functional approval for any post-cut-off changes, with stricter approvals needed for changes impacting production sequences. Third, Clear Ownership and Governance Cadence are defined, designating the Sales Operations team as accountable forecast owners and instituting regular accuracy review meetings. Together, these mechanisms transform forecasting from informal coordination into a disciplined process.

The implementation of this governance framework is structured into five sequential phases. These phases include defining governance rules and roles, developing standardized two-tier forecast templates, creating an exception management control mechanism, institutionalizing a regular governance meeting cadence, and establishing a quarterly performance monitoring forum for department heads. Potential implementation risks, such as resistance to the fixed forecast or incomplete exception approvals, are identified and mitigated. Mitigation strategies include allowing formally approved exceptions, ensuring transparency of the fixed production plan to prevent unauthorized changes, and enforcing forecast accuracy as a key performance indicator (KPI) to maintain accountability and learning from the process. Its core aim is not to directly enhance accuracy but to create a stable, controlled planning environment that enables consistent feasibility checks, reduces operational mismatches, and provides a foundation for subsequent improvements.

4.2. Second Stream - Development of Feasibility-Integrated Planning

Analysis reveals that forecast inaccuracy is predominantly driven by a mismatch between forecasted volume and operational feasibility. Recurring constraints in production capacity, SKU sequencing, and logistics readiness prevent forecasted call-offs from being shipped on time, resulting in systematic over-forecasting and large deviations. Currently, the forecast reflects only Sales intent, formulated without considering production limitations. This stream therefore focuses on integrating production feasibility into the forecasting process to align customer commitments with operational reality. To achieve this, the stream introduces a future-state planning model with explicit feasibility assessment. This model ensures the agreed Fixed Forecast (FF) consists only of call-offs that can be realistically produced and shipped, incorporating checks for overall production capacity, sequence, inventory, and logistics. A key feature is the differentiated call-off commitment, categorizing call-offs as confirmed, at-risk, or deferred based on their feasibility. This system includes a structured Sales escalation process, where deferred call-offs are escalated to the Sales team to assess Sales risk and decide between delaying the shipment or altering the production plan to accommodate the customer. The implementation is structured into four steps. First, defining common feasibility criteria and scope across all functions to establish a shared understanding. Second, developing capacity and sequencing visibility by having PPIC create a transparent "capacity-sequencing map." Third, establishing clear rules for re-phasing or partial commitment for deferred volumes, ensuring swift communication to customers. Fourth, institutionalizing feedback and continuous improvement by tracking the reasons for infeasible call-offs and managing customer portfolios to prevent repeated rescheduling for any single client. Despite careful planning, potential risks remain, including incomplete capacity data leading to incorrect decisions, conflicts between Sales and PPIC teams causing delays, and excessive conservatism from PPIC resulting in lost sales. Mitigation strategies involve starting with conservative data and refining it iteratively, using governance forums for faster conflict resolution, and allowing structured partial commitments and escalations as defined in the first stream. The core objective is to create a stable and controlled planning environment that enables consistent feasibility checks and reduces operational mismatch.

4.3. Third Stream - Development of Quantitative Forecast Enhancement

The objective of the third improvement stream is to enhance forecast accuracy by implementing a structured quantitative method, specifically the Holt-Winters model, to complement the current call-off-based approach. This will address the insufficiency of relying solely on near-term customer call-offs and provide PPIC with a reliable forward estimate for procuring raw materials 4-6 months in advance, allowing for only minor adjustments once final call-offs are received. This research employs the Holt-Winters formula to decompose demand into its three core components: level (baseline demand), trend (direction and rate of change), and seasonality (cyclical effects). To ensure optimization for ABC Company's data, the smoothing parameters (α, β, γ) are determined using Microsoft Excel's Solver, configured to minimize the sum of squared errors with the GRG Nonlinear method, thereby deriving parameters (α=0.2, β=0.1, γ=0.1) based purely on historical data fit. A forecast is then generated for January to December 2025 using full-year 2024 data to capture key seasonal patterns. The results, demonstrate that the Holt-Winters forecast aligns more closely with actual sales than ABC Company's current forecast, indicating a promising improvement despite the limitation of a short historical data timeframe which necessitates further iteration and validation.

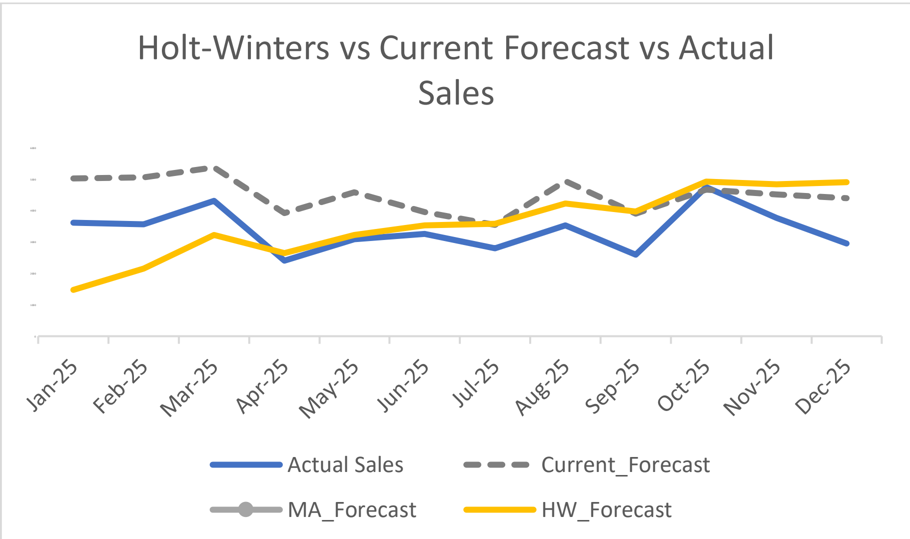

Figure 6. Holt-Winters vs Current Forecast vs Actual Sales in 2025

Several potential risks associated with this enhanced forecasting method are identified. These include parameter misspecification leading to increased error, poor data quality distorting seasonality, misinterpretation of performance metrics causing conflicting decisions, and overconfidence in the model reducing market responsiveness. Corresponding mitigation strategies involve rigorous back-testing, data validation, standardizing key performance metrics, and positioning Holt-Winters as a baseline to be combined with market intelligence and expert judgment. This stream provides a robust quantitative foundation for more accurate long-term planning.

4.4. Fourth Stream - Development of Integration of Expert Judgement

The fourth and final improvement stream integrates expert judgment to account for external factors like Sales negotiations and market intelligence, which cannot be captured by historical data alone. This process is structured into defined steps: using the Holt-Winters forecast from Stream 3 as a quantitative baseline, selecting key experts (Head of Sales, Head of Sales Operations, and Head of PPIC) based on their deep customer and operational knowledge, and assigning them credibility weights (0.4, 0.25, and 0.35 respectively) derived from their experience and domain expertise. A model trust factor (α) of 0.5 is set, reflecting the recent low forecast accuracy, and strict governance requires all expert adjustments to be submitted before the monthly cut-off to preserve process stability.

The integration is executed using the Expert Knowledge Integration (EKE) method, which calculates a final forecast by blending the weighted Holt-Winters baseline (with a 0.5 trust factor) with the weighted expert judgment (with a complementary 0.5 factor). The results for 2025, show the EKE forecast significantly closing the gap to actual sales compared to previous methods. As illustrated in Figure IV.8, the EKE method achieves the highest accuracy for ABC Company, with a MAPE of 25.55%, an RMSE of 30% of the total sales, and a Bias of 10.17%, outperforming both the original call-off forecast and the standalone Holt-Winters model, despite a residual gap in December 2025 attributed to port congestion and a sudden year-end policy change.

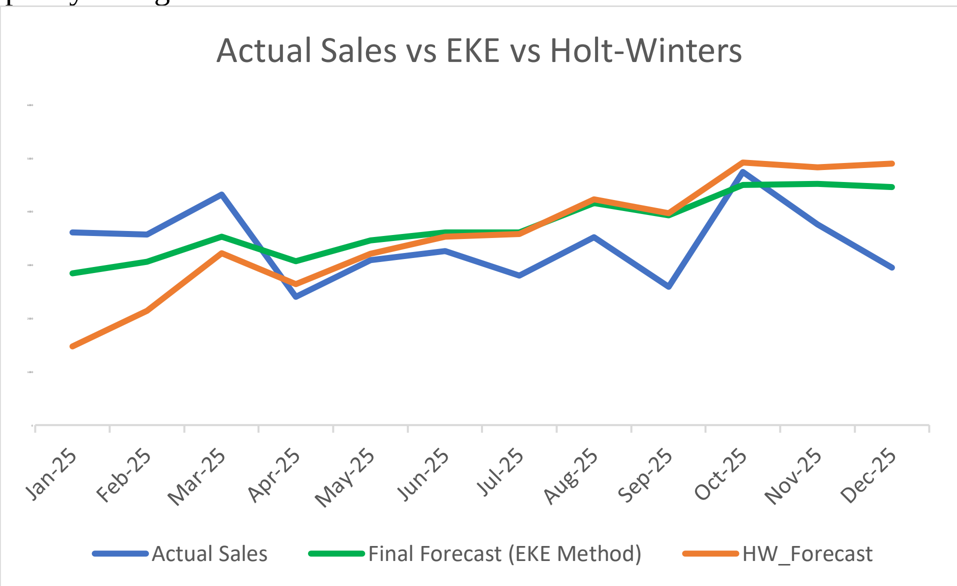

Figure 7. Actual Sales vs EKE vs Holt-Winters in 2025

However, this method introduces specific risks, including subjective bias from departmental agendas, potential execution instability from late adjustments, and process fatigue from over-complexity. Corresponding mitigation strategies involve the routine evaluation of expert weights, strict enforcement of submission cut-offs with mutual scheduling agreements, and limiting criteria while standardizing templates to streamline the process. With the enhanced forecasting system now validated, the subsequent focus shifts to the control phase, aimed at institutionalizing these improvements.

5. Control Phase

The control phase is designed to ensure the sustainability, monitoring, and continuous improvement of the validated enhancements. While the four streams have successfully stabilized governance, integrated feasibility, and improved accuracy, a persistent 10% positive forecast bias indicates the necessity for ongoing control mechanisms. This phase therefore focuses not only on maintaining accuracy but also on actively correcting this bias over time. To facilitate this control, the primary Critical-to-Quality (CTQ) metric—forecast accuracy—is decomposed into three specific, controllable dimensions with defined targets: MAPE for accuracy (target <30% of actual sales), RMSE for error magnitude (target <30% of actual sales in tons), and Forecast Bias for systematic deviation (target within ±10%). Accountability is established through a comprehensive RACI matrix that clarifies roles across the forecasting lifecycle. A dedicated manager from the Sales Operations team is designated as the Forecast Owner, accountable for the overall process, while responsibilities for specific activities like call-off input, feasibility validation, and corrective actions are clearly assigned to relevant functions to prevent fragmented ownership.

Standardization is enforced through the creation of formal Standard Operating Procedures (SOPs) to institutionalize the new processes. Key SOPs mandate the use of the Holt-Winters model as the mandatory baseline with annual parameter reviews, define rules for expert adjustments and bias thresholds, enforce a fixed monthly forecast freeze on the mi with a defined adjustment window, and establish regular post-period reviews including monthly forecasting assessments and quarterly performance evaluations with root cause logging for biases. An implementation roadmap, detailed in a Gantt Chart, outlines the phased and sequential deployment of these improvements. The logic follows a deliberate order: first establishing governance and feasibility controls to create process discipline, then introducing the quantitative forecasting method, followed by the integration of expert judgment. The control mechanisms themselves, including KPI monitoring and SOP enforcement, are implemented only after the core forecasting process is stabilized, thereby minimizing implementation risk. A defined review cadence ensures continuous oversight and adaptation. Key activities are assigned regular frequencies and clear ownership: the Forecast Owner is responsible for monthly forecast generation, Sales Operations for monthly expert adjustments, Management for semi-annual forecast freeze reviews, and PPIC for annual post-period reviews. This structured approach ensures the improvements are embedded into the organizational routine, promoting long-term sustainability and the ongoing correction of forecast bias.

CONCLUSION AND RECOMMENDATION

Conclusion

This research concludes that the low accuracy of sales forecasts at ABC Company is not attributable to a single factor but stems from a combination of interrelated process, governance, behavioral, and execution-related issues. The primary factors include a lack of clear governance and ownership, leading to an unstable forecast with inconsistent interpretations and weak accountability. A critical structural misalignment exists where the Sales team views customer call-off as a firm commitment, while the production team treats it as a tentative signal, resulting in systematic over-forecasting and frequent delays. Furthermore, execution feasibility concerning production sequencing, and vessel availability is not integrated into the forecasting process. The informal and unstructured application of expert judgment introduces optimism bias, and the absence of an accountable, objective forecasting method allows discussions to be dominated by Sales expectations rather than demand patterns. Together, these factors explain the high MAPE, high RMSE, and persistent positive bias observed. To address these root causes, the research demonstrates that a systemic redesign of the forecasting process is required, implemented through four interrelated improvement streams. First, forecast governance is established to ensure stability by appointing a single forecast owner, enforcing a formal forecast freeze, creating SOPs, and defining a clear RACI matrix. Second, production feasibility is integrated into the forecast approval, not treated as an afterthought, to bridge the gap between planned demand and executable output. Third, the quantitative forecasting method is enhanced using the Holt-Winters exponential smoothing model, which shows significantly improved accuracy, though it requires regular parameter evaluation. Fourth, expert judgment is incorporated in a structured and governed manner using the EKE method, with predefined weighting and approval mechanisms to add value while controlling bias. The research further concludes that there is no single "best" forecasting technique in isolation for ABC Company. The most effective solution is a hybrid approach that balances quantitative and qualitative insights. The Holt-Winters method is well-suited to capture the inherent trend and seasonality of the business. However, given limitations in historical data and the need for market intelligence, it must be complemented by the structured integration of expert judgment via the EKE method. This combination allows ABC Company to leverage statistical patterns while remaining responsive to the latest market movements in the volatile FMCG sector. Sustainable improvement requires the institutionalization of these changes through robust control mechanisms. This involves the regular monitoring of CTQs (MAPE, Bias, RMSE), a defined review cadence, corrective action protocols, and ongoing performance evaluation. These measures ensure early detection of deviations and prompt correction, embedding the improvements into the organizational routine for long-term sustainability and continuous enhancement of forecast accuracy.

Recommendations

Based on the research findings, ABC Company should institutionalize forecast governance as a core operational discipline. This requires formally appointing a single forecast owner, consistently applying the defined RACI structure, and treating the forecast freeze and exception process with the same rigor as financial planning. Without embedding this governance, there is a high risk of reverting to the previous reactive and negotiation-driven forecasting behavior. The company must further strengthen the integration of execution feasibility by evolving it from a post-forecast validation step into a proactive decision-support function. This involves translating production sequencing constraints into simplified, early visibility tools for Sales teams, enabling Sales Operations to manage customer expectations based on operational realities in advance, thereby reducing post-cut-off conflicts and reactive adjustments. ABC Company needs to establish a structured learning mechanism to continuously refine its hybrid forecasting approach. For the quantitative Holt-Winters model, this entails conducting frequent parameter reviews to maintain its accuracy and cross-functional trust as trends evolve. For the qualitative EKE method, it requires retrospectively reviewing expert adjustments against actual outcomes and recalibrating expert weights, especially during organizational changes, to promote transparency and sustained accountability.

Beyond traditional accuracy metrics, management should actively monitor forecast bias as a leading indicator of process health. Persistent positive or negative bias often signals underlying organizational behaviors, such as systematic optimism or a lack of execution confidence. Proactively interpreting and addressing the root causes of this bias allows for more fundamental corrections than merely reacting to numerical error deviations. In summary, these recommendations underscore that sustainable forecast improvement hinges on prioritizing discipline before sophistication. ABC Company must first ensure strong governance, seamless feasibility integration, structured judgment, and controlled quantitative validation. By following this progression, the company can systematically transform forecasting into a reliable capability that supports stable execution, informed decision-making, and long-term performance.

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