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Improving Inventory Management to Prevent Stockout and Overstock: A Case Study Esa Frozen Ramen

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Abstract - *This study examines inventory management challenges at Esa Frozen Ramen, a local frozen food MSME, focusing on stockout and overstock problems. Between May 2024 and June 2025, Esa experienced more than 120 stockouts and 16 units of unsellable overstock, causing losses exceeding Rp4,500,000. The root causes were the absence of structured inventory planning and lack of data-driven forecasting. Using weekly historical demand data (54 weeks), the research compared three time series forecasting methods: Simple Moving Average (SMA), Weighted Moving Average (WMA), and Single Exponential Smoothing (SES), with WMA (0.1, 0.9) achieving the best accuracy (MAD = 1.49, MSE = 6.43, MAPE = 9%). The selected model was used retrospectively to calculate Economic Order Quantity (EOQ), Safety Stock, and Reorder Point (ROP), yielding optimal values of 33 units, 2 units, and 8 units respectively. This integrated approach offers Esa a practical and low-cost strategy to minimize inventory risks, improve product availability, and enhance operational efficiency*

Keywords - *Inventory Management, Frozen Food, Demand Forecasting, Economic Order Quantity, Safety Stock, Reorder Point*

I. INTRODUCTION

A. *Research Background*

The frozen food industry in Indonesia has shown significant growth, valued at over IDR 200 trillion in 2024 and projected to grow at a 7.5% CAGR from 2025 to 2030 [1], driven by urban lifestyles, rising middle-class income, and the expansion of cold-chain logistics [2]. In this competitive market, inventory management is crucial for balancing supply and demand while minimizing operational costs [3]. For perishable products such as frozen ramen, poor inventory control can lead to stockouts and resulting in lost sales and customer dissatisfaction or overstocks can increase holding costs and lead to spoilage [4].

Esa Niskala Jaya, operating under the brand Semangkoek, produces frozen ramen through outsourcing to a third-party vendor. Despite product quality advantages, the business faces frequent stockouts during high demand and occasional overstock due to its short shelf life of three months. Between May 2024 and June 2025, these issues caused more than 120 stockouts or lost Rp4,500,000 of potential revenue and 16 units of unsellable overstock, leading to significant financial losses more than Rp5,000,000.

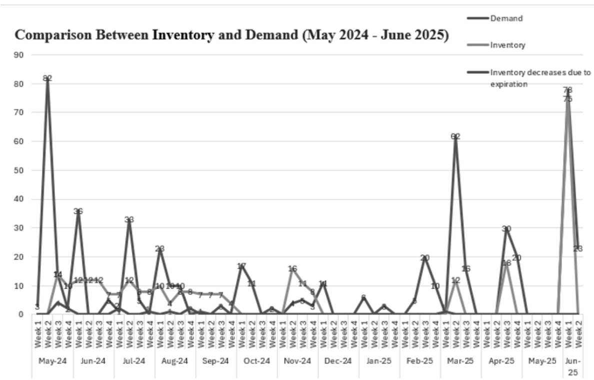

Figure 1 Graph of Esa's Data Demand and Data Inventory

This study therefore aims to identify the key factors contributing to these inventory imbalances and determine the most suitable inventory management strategy to minimize them, specifically addressing the underlying causes of both stockouts and overstocks in Esa's operations.

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II. METHODOLOGY

A. Literature Review

1. Inventory Management

Inventory management plays a critical role in ensuring product availability and operational efficiency, especially in industries with volatile demand and perishability constraints [5]. Effective inventory management minimizes stock imbalances and costs while maintaining service levels [6].

2. Demand Forecasting

Demand forecasting serves as the basis for production planning and inventory control by predicting future demand using historical data [7]. Forecasting methods include qualitative, causal, simulation, and time series approaches, with time series being most suitable when sufficient historical demand data exists and external factors are minimal [8].

Time series methods applied in this study include:

1) Simple Moving Average (SMA) calculates the unweighted mean of past demand over a fixed window, effective for smoothing random variations without trend or seasonality [3].

$$A_t = \frac{D_t + D_{t-1} + D_{t-2} + ..D_{t-n+1}}{n} \quad (1)$$

2) Weighted Moving Average (WMA), similar to SMA but assigns higher weights to recent periods, making it more responsive to demand changes [8].

$$A_t = W_1(D_t) + W_2(D_{t-1}) + W_3(D_{t-2}) + .. + W_n(D_{t-n}) \quad (2)$$

3) Single Exponential Smoothing (SES) uses a smoothing constant α (0–1) to combine the latest demand and previous forecast, suitable for stable data without strong trends or seasonality [9].

$$A_t = \propto D_t + (1 - \propto) A_{t-1} \quad (3)$$

Forecast error measurement determines model accuracy using Mean Squared Error (MSE), Mean Absolute Deviation (MAD), and Mean Absolute Percentage Error (MAPE), with lower values indicating higher accuracy [8]. The formula:

$$MSE = \frac{\sum E_t^2}{n} \quad (4)$$

$$MAD = \frac{\sum |E_t|}{n} \quad (5)$$

$$MAPE = \frac{\sum(|E_t|/D_t)100}{n} \quad (6)$$

3. Inventory Control Models

To manage inventory effectively, several classical models are applied to determine optimal order quantities, safety buffers, and reorder timing.

1) Economic Order Quantity (EOQ) determines the optimal order size to minimize total ordering and holding costs, assuming stable demand, constant lead time, full order delivery, and no quantity discounts [10].

$$EOQ = \sqrt{\frac{2DS}{H}} \quad (7)$$

2) Safety stock provides a buffer against variability in demand or lead time, assuming demand fluctuations follow a normal distribution and lead time variability can be estimated from historical data [3].

$$Safety\ Stock = Z \times \sigma_{dLT} \quad (8)$$

3) Reorder Point (ROP), specifies the stock level at which a replenishment order should be placed, incorporating average demand during lead time plus safety stock, assuming consistent lead time and known demand rates [8].

$$ROP = (Average\ Daily\ Demand \times Lead\ Time) + Safety\ Stock \quad (9)$$

4. Previous Research Study

Several studies have explored the application of Economic Order Quantity (EOQ) and demand forecasting in managing perishable and frozen food inventories, showing that integration of forecasting and order planning can reduce stock imbalances. However, gaps remain in existing literature. Some works [11] and [12] focus on theoretical or simulation-based models with limited real-world MSME applications. Others [13] emphasize food safety without addressing inventory imbalance issues. Research by [14] and [15] lacks either comprehensive accuracy evaluation or clear integration between forecasting outputs and inventory decision models. These gaps indicate the need for an applied and integrated approach tailored to MSME characteristics.

B. Research Methodology

The research methodology is designed with several stages of process can be seen on Figure 2

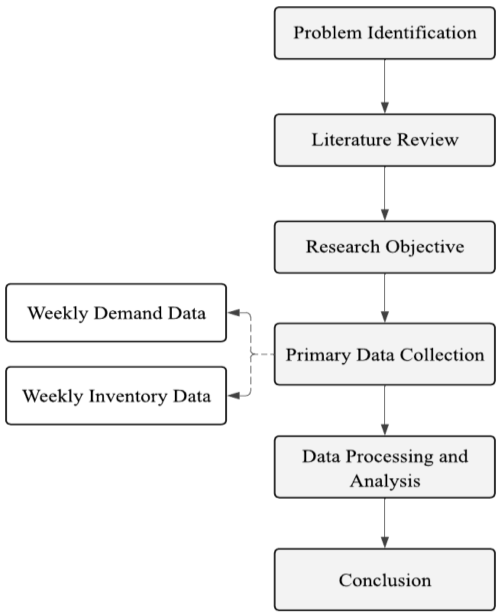

Figure 2 Research Methodology

This study adopts a descriptive quantitative case study approach. Primary data were collected from Esa's operational records over 54 weeks (May 2024 - June 2025). The data included weekly actual demand and inventory levels, allowing identification of stockout and overstock periods. Forecasting methods (SMA, WMA, SES) were applied retrospectively, not for predicting future demand, but to simulate how a forecast-based strategy would have performed compared to the existing judgment-based approach [16]. The most accurate method was then used to calculate EOQ, Safety Stock, and ROP, enabling a comparative cost and performance evaluation.

III. FINDINGS AND DISCUSSION

A. Root Cause Analysis

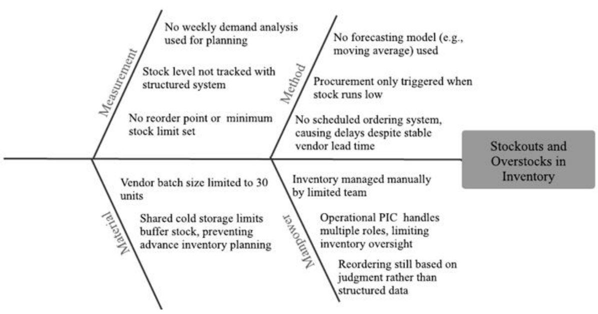

Figure 3 Fishbone Diagram

The root cause analysis using a fishbone diagram revealed in Figure 3.1 that the main constraint in Esa's inventory management is the absence of structured, data-driven forecasting and inventory control. Although historical demand data exists, it is underutilized for planning, and procurement decisions rely on judgment rather than systematic models such as EOQ, safety stock, and ROP. This leads to inconsistent ordering, frequent stockouts, and occasional overstocks, resulting in financial losses and reduced operational efficiency.

B. Demand Pattern Identification

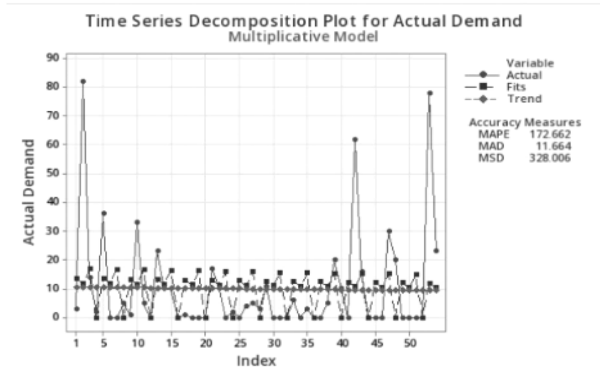

Figure 4 Time Series Decomposition

Esa's weekly demand data from May 2024 to June 2025 showed high fluctuations with occasional sharp peaks and drops. Time series decomposition using a 4-week Simple Moving Average that visualized in Figure 3.2 revealed no significant trend or seasonality, confirming the data is stationary. This justified the use of Simple Moving Average (SMA), Weighted Moving Average (WMA), and Single Exponential Smoothing (SES) as forecasting methods [3].

1. Forecasting Analysis

1) Simple Moving Average (SMA)

Tested window sizes 2, 3, and 4 weeks. The 2-week window gave the lowest errors (MAD 7.45; MSE 160.66; MAPE 44%) but was less responsive to sharp demand changes due to equal weighting.

Table I Forecast Error Measurement - SMA)

Error	2 Weeks	3 Weeks	4 Weeks
MAD	7.4528	8.33974	8.2156
MSE	160.660	177.134	176.921
MAPE	44%	65%	60%

2) Weighted Moving Average (WMA)

Weights optimized with Solver, constrained to ≥ 0.1. The (0.1; 0.9) configuration gave the best performance (MAD 1.49; MSE 6.43; MAPE 9%), showing high responsiveness suitable for short-life products.

Table II Forecast Error Measurement - (WMA)

Error	Weight I: (0.1, 0.9)	Weight II: (0.1, 0.1, 0.8)	Weight III: (0.1, 0.1, 0.1, 0.7)
MAD	1.4905	2.5019	3.2862
MSE	6,4264	15,942	28.307
MAPE	9%	20%	24%

3) Single Exponential Smoothing (SES)

Optimized α = 0.05097, producing overly smooth forecasts and very high errors (MAPE 169%), making it unsuitable for highly fluctuating demand.

Table III Forecast Error Measurement - (SES)

σ =0,05097		
MAD	MSE	MAPE
10.8933	350,594	169%

In conclusion, the WMA (0.1; 0.9) method outperformed SMA and SES, offering the best accuracy and adaptability for perishable goods inventory management [17]. This model was selected as the basis for inventory control calculations.

2. Inventory Models Calculations

A forecasting-based inventory control method was applied to address Esa's inventory management issue. After evaluating several forecasting models based on error measurements, the Weighted Moving Average (WMA) method was chosen for demand forecasting due to the most accurate results. The forecasted demand becomes the basis for determining the optimal order quantity, safety stock, and reorder point to create a sufficient inventory system. Annual demand (D) from WMA forecasts was 517 units. Using ordering cost (S) of Rp25,000 per order and annual holding cost (H) of Rp24,000/unit per year:

Table IV EOQ Model Calculation

S	D	H	EOQ
Rp25,000	517	Rp24,000	33

Based on Table 3.4, the optimal order quantity for Esa is approximately 33 units/order. However, the standard EOQ model works under the assumption of constant demand, which does not fully represent the actual conditions of Esa, where demand varies significantly. Safety stock is calculated to buffer the demand variability with a service level of 90%. Then, σ using the standard deviation of weekly forecasted demand, which is 2.2290 units, and the lead time for ordering to product arrival was identified as 4 days, or 0,75 weeks. So that the safety stock is calculated as in Table 3.5:

Table V Safety Stock Calculation

Z	σ	$\sqrt{L}$	Safety Stock
1.28	2.2290	0.7549	2

The result based on Table 3.5 was 2 units as a sufficient inventory buffer. After calculating the EOQ and safety stock, the next step is determining the Reorder Point (ROP). Based on the WMA forecast, the average weekly demand was determined to be 9.9519 units from the annual average of 517 units. With a lead time of 0.57 weeks and adding the safety stock of 2 units. The results were shown in Table 3.6, which the ROP approximately 8 units.

Table VI Reorder Point Calculation

Average Weekly Demand	Lead Time	Safety Stock	ROP
9.9519	0.5714	2	8

3. Comparative Analysis of Forecast-Based and Actual-Based

To evaluate the effectiveness of the forecasting-based inventory strategy, a comparative analysis was conducted between Esa's judgment-based approach (non-calculated) inventory practice and the forecasting-based model using Weighted Moving Average (WMA). To ensure fairness, both strategies were compared using the same data range (week 2 to 53) and cost parameters. This alignment eliminates bias due to differing time intervals and ensures a consistent evaluation basis.

Table VII Comparison Of EOQ

Based Data	S	D	H	EOQ
Forecast Based	Rp25,000	517	Rp24,000	33
Actual Based	Judgment-based approach (no-calculation)			25

Based on Table 3.7 the higher EOQ in the forecast-based approach reduces ordering frequency and lowers the risk of stockouts, while the actual-based approach orders more frequently and is more prone to shortages.

Table VIII Comparison Of Safety Stock

Based Data	Z	σ	$\sqrt{L}$	Safety Stock
EOQ	1.28	2.2290	0.7549	2
Actual Based	Judgment-based approach (no-calculation)			≤5

Although the forecast-based safety stock appears smaller on Table 3.8, it is more data-driven and cost-efficient, tailored to actual uncertainty captured through forecasting because the actual-based does not use a formal calculation but typically sets inconsistent units or 5 or fewer units as a buffer based on experience, which may not be sufficient to cover the unexpected demand fluctuations, and it will cause a stockout due to the inconsistent safety stock units.

Table IX Comparison Oreorder Point (ROP)

Based Data	Average Weekly Demand	Lead Time	Safety Stock	ROP
EOQ	9.9519	0.5714	2	8
Actual Based	Judgment-based approach (no-calculation)			0

Lastly, the comparison of reorder points based on Table 3.9 the discrepancy becomes even more evident and highlights the strategic advantage of forecast-based ROP, which allows Esa to anticipate replenishment needs more accurately and reduce the risk of stockout or overstock. Also, the absence of structured ROP calculation limits Esa's ability to maintain the consistency of product availability

Table X Comparison Of Total Inventory Cost

Component	EOQ	Actual-Basec
D	517	450
Q	33	25
S	Rp25,000	Rp25,000
H	Rp24,000	Rp24,000
Ordering Cost Component (OC=D/Q*S)	Rp394,01ɛ	Rp450,000
Holding Cost Component (HC=Q/2*H)	Rp394,01ɛ	Rp300,000
Total Inventory Cost (TIC=OC+HC)	Rp788,03€	Rp750,000

In terms of cost analysis based on Table 3.10, the total inventory cost of the forecast-based slightly higher than the actual-based and the difference is Rp38,036. This result is primarily due to the larger EOQ in the forecast-based model, which increases the holding cost component. However, the forecast-based approach reduces the ordering frequency, which lowers the ordering cost per year also reduces the total number of orders per year, leading to a lower annual ordering cost compared to the actual-based strategy. This trade-off reflects the balance between holding and ordering costs that the EOQ model aims to optimize.

So that, the forecast-based system using WMA combined with EOQ, safety stock, and ROP provides a more consistent, data-driven, and scalable inventory management strategy. Compared to the unstructured actual-based approach, it better ensures product availability and minimizes both stockout and overstock risks.

IV. CONCLUSION

Through a comprehensive analysis of Esa's internal operational data and the application of demand forecasting and inventory control models, this study identified that stockouts and overstocks mainly result from the absence of structured inventory planning and data-driven forecasting. Procurement decisions were previously made manually without standardized records, with demand data scattered across spreadsheets and chats, leading to inconsistent planning. This caused frequent stockouts and overstocks, while the lack of models such as EOQ, safety stock, and ROP further weakened procurement timing despite consistent vendor lead times.

The most suitable strategy is to integrate an inventory control model based on retrospective demand forecasting. Using the Weighted Moving Average (WMA) method with Solver-optimized weights (0.1, 0.9), the most accurate forecast was obtained, resulting in EOQ of 33 units, safety stock of 2 units, and ROP of 8 units. Although not intended for real-time forecasting, this approach offers a structured, data-driven alternative to the current judgment-based system, reducing inventory risks, improving product availability, and lowering holding costs, particularly effective for small businesses with limited storage and perishable products.

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