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Forecasting–Inventory Optimization Model: Integrating Exponential Smoothing with Min–Max and Blanket Order Systems

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ABSTRACT

The research integrates demand forecasting using the Exponential Smoothing (ES) method to develop an adaptive and data-driven framework for cost optimization in volatile demand conditions. A quantitative–descriptive and analytical approach was adopted by combining forecasting accuracy analysis with cost comparison modeling. Two forecasting models—Moving Average (MA) and Exponential Smoothing (ES)—were tested using 2021–2023 demand data. The most accurate model (lowest MAPE) was used to simulate inventory performance through the Min–Max and Blanket Order systems. Sensitivity analysis with ±10% demand variation was conducted to evaluate model robustness, while correlation testing validated forecast accuracy against actual demand. The Exponential Smoothing model achieved superior predictive accuracy (MAPE = 0.883%) compared with the Moving Average model (MAPE = 1.338%). The Min–Max Stock system produced lower total costs—IDR 116,269,920 (2021), IDR 123,260,400 (2022), and IDR 128,466,720 (2023)—compared with the Blanket Order system, which recorded higher and more volatile costs across the same period. The hybrid Min–Max–Forecasting approach demonstrated higher stability under demand fluctuations and improved procurement efficiency, achieving an estimated 30% cost reduction. This study offers SMEs an evidence-based strategy for integrating forecasting accuracy into inventory control, supporting cost reduction and production continuity in resource-constrained environments. The model can be adopted as a reference for developing adaptive inventory policies within the Indonesian SME food sector. The originality of this study lies in its hybrid integration of Exponential Smoothing forecasting within comparative Min–Max and Blanket Order frameworks, offering empirical validation for forecasting-driven inventory decisions at the SME scale. The approach provides both theoretical advancement and managerial relevance by aligning predictive accuracy with inventory cost optimization in volatile market contexts.

Keywords: Inventory control, Min–Max method, Blanket Order, Exponential Smoothing, SMEs, Forecasting accuracy, Cost optimization.

INTRODUCTION

Raw material inventory control plays a pivotal role in ensuring the operational stability and cost efficiency of manufacturing industries, particularly in the food sector, where production continuity depends heavily on the consistent availability of ingredients. For small and medium-sized enterprises (SMEs), inaccurate inventory management can directly affect production schedules, product quality, and overall profitability. According to [1], weak inventory control systems often lead to excessive resource consumption due to overstock or stockout conditions, which in turn hinder production targets and increase total inventory costs [2].

This phenomenon is evident in SMEs, a snack manufacturer, the company experienced significant fluctuations in monthly demand, with an average chili requirement of approximately 700 kg per month, ranging between 682.20 kg and 732.54 kg. These fluctuations generated two major issues: (1) stockout events during high-demand periods, disrupting production flow and creating backorders, and (2) overstock accumulation during periods of low sales, resulting in additional storage costs of around IDR 250,000 per month. Furthermore, the fixed ordering cost of IDR 200,000 per cycle increased the total expenditure, as orders were placed repeatedly without standardized planning or demand forecasting.

Such evidence indicates that the existing inventory control system remains reactive and lacks a structured forecasting approach to determine optimal stock levels. As highlighted by [3], [4], effective inventory control depends on the organization's ability to forecast demand accurately and establish appropriate reorder points. In the case of Maisatun SMEs, inconsistent demand for fresh chili has made it difficult to define safety stock, minimum stock, and reorder points effectively. Consequently, procurement decisions are often made without considering historical demand patterns, leading to higher overall inventory costs and inefficient cash flow [5].

Previous studies have extensively explored inventory control methods such as the Economic Order Quantity (EOQ), Material Requirement Planning (MRP), and Continuous Review System models. However, these methods were primarily designed for large-scale industries with relatively stable demand characteristics. In contrast, SMEs that face seasonal and volatile market demand require more adaptive and flexible inventory control strategies. The Min-Max Stock method focuses on maintaining stock within a predetermined safety range to prevent shortages and surpluses [6], [7], while the Blanket Order method facilitates bulk purchasing agreements at fixed prices within a defined period [8]. Despite their practical advantages, there remains a research gap concerning the comparative cost-effectiveness of these two methods when applied to SMEs with fluctuating demand and constrained resources. Moreover, most prior studies have not incorporated forecasting accuracy as a determinant factor in choosing the most cost-efficient control model.

Therefore, this study aims to analyze and compare the effectiveness of the Min-Max Stock and Blanket Order methods in minimizing total raw-material inventory costs at SMEs Keripik Cabai Maisatun. By integrating demand forecasting using the Exponential Smoothing method—which demonstrated the smallest error with a MAPE of 0.883%, compared with the Moving Average method (1.338%)—this research proposes a data-driven and cost-oriented inventory control strategy. The findings are expected to contribute to the advancement of empirical studies on SME-scale inventory management, provide validation for hybrid forecasting-control approaches, and offer managerial implications for achieving sustainable cost optimization and production reliability within volatile market environments.

METHOD

This research adopts a quantitative–descriptive and analytical framework designed to evaluate the efficiency of inventory control strategies in minimizing total costs within small and medium-sized enterprises (SMEs). The study integrates a forecasting–inventory modeling hybrid design, combining demand prediction with two distinct control systems: the Min–Max Stock Method and the Blanket Order Method [9], [10]. This dual approach allows comprehensive analysis of inventory cost behavior under fluctuating demand patterns.

The overall framework aims to:

(1) forecast demand for chili-based raw materials with high accuracy;

(2) compute total inventory costs using Min–Max and Blanket Order methods; and

(3) determine the optimal approach based on comparative cost minimization.

The framework aligns with prior quantitative models proposed by [11], [12], [13]and adapted for SMEs' operational characteristics with constrained resources, fluctuating supplier lead times, and limited technological support.

Data Characteristics and Variables

This study utilized a combination of primary and secondary data:

- Primary Data: Direct observations of the inventory flow, interviews with production and purchasing personnel, and on-site evaluation of order cycles and stock fluctuation patterns.
- Secondary Data: Historical quantitative records from January 2021 to December 2023, comprising:
  - Monthly chili demand (kg);
  - Purchase quantity and frequency;
  - Unit purchasing price (Rp/kg);
  - Ordering cost and holding cost per cycle;
  - Supplier lead time (days).

The study focuses on five major variables that influence total inventory costs: demand (D), order cost (C_o), holding cost (C_h), purchasing cost (C_p), and safety stock (SS).

Forecasting Analysis

Forecasting serves as the initial analytical stage to estimate future demand and form the basis for subsequent inventory computations. Two **time-series forecasting models** were tested [14], [15]:

1. Moving Average (MA, n=3) assumes equal weighting across historical periods.
2. Single Exponential Smoothing (ES, α=1) provides adaptive weighting emphasizing recent observations.

To evaluate the forecasting performance, three standard accuracy metrics were applied:

- Mean Absolute Deviation (MAD) measures absolute forecast deviation;
- Mean Squared Error (MSE) penalizes large forecast errors;
- Mean Absolute Percentage Error (MAPE) assesses relative forecast precision.

The forecasting model with the smallest MAPE was selected as the optimal predictor of monthly chili demand and used as the input for inventory control simulations.

Comparative and Sensitivity Analysis

A comparative cost analysis was performed to determine which model Min–Max or Blanket Order provides the lowest total inventory cost (TC_1 vs. TC_2). Additionally, a sensitivity test was conducted by simulating ±10% demand variation to assess model robustness under uncertainty. Statistical validation included correlation analysis between forecasted and actual demand, as well as percentage cost reduction benchmarking. This step ensured that selected models maintained reliability and adaptability under real production conditions [16], [17].

RESULTS

The monthly demand trend for Chips throughout the year 2023. The dataset represents the actual sales quantity observed across twelve months, providing an overview of seasonal demand fluctuations and overall market growth dynamics. The analysis aims to identify periods of high and low demand to support production planning, inventory control, and supply chain optimization. Consistent demand growth is a critical indicator of stable consumer preference and effective distribution strategy within the snack industry.

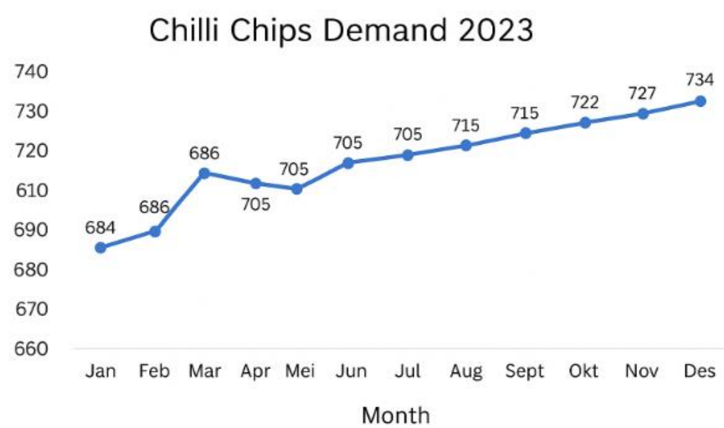

Figure 1. Plot Data

Based on Figure 1, the demand trend shows a gradual increase throughout the year with minor fluctuations in the first quarter. Demand rose sharply from February to March, reaching approximately 710 units, followed by a slight stabilization from April to May. From June onward, the trend continued upward, indicating sustained market absorption and improved consumer acceptance. The highest demand was recorded in December, exceeding 730 units, reflecting strong end-of-year sales momentum. These findings suggest that production capacity should be adjusted to anticipate peak demand periods, particularly during the final quarter, to maintain market responsiveness and minimize stock shortages.

Moving Average (MA)

Figure 2 displays the demand forecasting results using the Moving Average (MA) method. This technique estimates future values by averaging a fixed number of preceding data points, thereby minimizing short-term fluctuations and emphasizing the underlying demand trend. In this study, a three-period moving average (n = 3) was implemented using Microsoft Excel 2019 to analyze the monthly demand pattern of Chilli Chips during 2023. The approach aims to evaluate the stability of the demand series and the forecasting precision through performance indicators such as MAPE, MAD, and MSE.

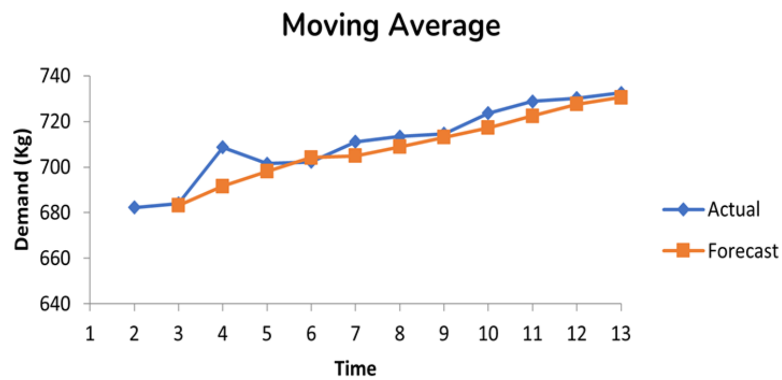

Figure 2. Moving Average Forcasting

As shown in Figure 2, the forecasted demand generated by the Moving Average model closely follows the actual demand pattern, with minor deviations observed during the early periods. The forecast trend line successfully captures the general upward trajectory of demand throughout the year. The resulting accuracy metrics demonstrate satisfactory performance, yielding a Mean Absolute Percentage Error (MAPE) of 1.338%, a Mean Absolute Deviation (MAD) of 9.577, and a Mean Squared Error (MSE) of 125.203. These results indicate that the Moving Average method provides an acceptable level of predictive accuracy for short-term forecasting, making it an effective tool for production planning and inventory control in relatively stable demand environments.

Exponential Smoothing

Figure 3 presents the forecasting results obtained using the Exponential Smoothing (ES) method. This method applies a weighted average to past observations, where more recent data points receive higher significance through a smoothing constant (α). The Exponential Smoothing model is effective for capturing short-term demand fluctuations while maintaining trend stability. In this analysis, the forecasting process was conducted with a smoothing constant of α = 1 to evaluate its predictive performance in modeling the monthly demand pattern of Chilli Chips during 2023.

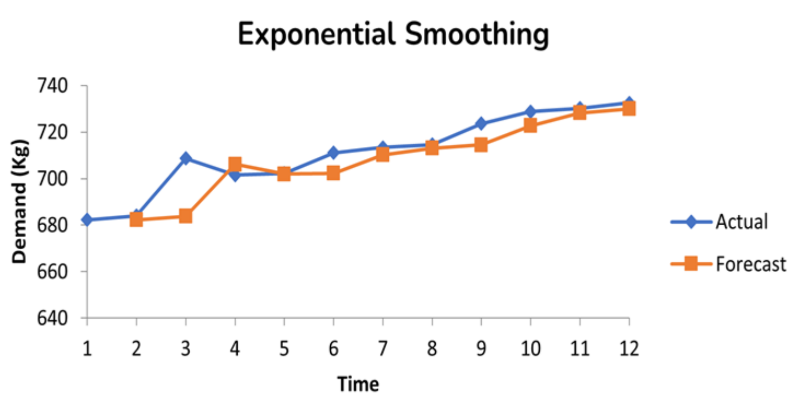

Figure 3. Exponential Smoothing

The results shown in Figure 4 demonstrate a close alignment between the actual and forecasted demand curves, confirming the model's capability to accurately represent demand behavior. The calculated performance metrics indicate a high forecasting accuracy, with a Mean Absolute Percentage Error (MAPE) of 0.883%, a Mean Absolute Deviation (MAD) of 5.896, and a Mean Squared Error (MSE) of 78.245. These low error values confirm that the Exponential Smoothing model provides a reliable fit for short-term demand forecasting. Overall, this method effectively smooths random variations and captures the upward trend in demand, making it suitable for operational decision-making in production and inventory management.

Min-Max

Table 1 presents the results of the Min–Max Inventory Control Method applied to raw material management over the period 2021–2023. This method determines the minimum and maximum stock levels necessary to maintain an optimal balance between inventory availability and cost efficiency. The Min–Max policy establishes two control limits—Minimum Stock (to prevent stockouts) and Maximum Stock (to avoid excessive holding)—which are adjusted based on annual consumption, lead time, and safety stock requirements. The calculations were performed under the assumption of fixed ordering and holding costs per year to facilitate consistent evaluation and decision-making across periods.

Table 1. Results of Min-Max Method for Raw Materials

Parameter	2021	2022	2023
Safety Stock	29.215 Kg	48.12 Kg	2.,48 Kg
Minimum Stock	659.94 Kg	701.55 Kg	732.54 Kg
Maximum Stock	1.262 Kg	1.307 Kg	1.422 Kg
ROP	659.94 Kg	701.55 Kg	732.54 Kg
Order Frequency	11 times	12 times	12 times
Total Cost	**IDR 116,269,920**	**IDR 123,260,400**	**IDR 128,466,720**

As observed in Table 1, the safety stock and inventory levels experienced moderate fluctuations over the three-year period. The minimum stock increased from 659.94 kg in 2021 to 732.54 kg in 2023, while the maximum stock rose proportionally from 1,262 kg to 1,422 kg, indicating gradual growth in production requirements. The order frequency stabilized at 12 orders per year in both 2022 and 2023, suggesting improved procurement efficiency and demand predictability. Correspondingly, the total inventory cost showed a steady increase from IDR 116,269,920 in 2021 to IDR 128,466,720 in 2023, reflecting higher material utilization and storage needs. Overall, the Min–Max approach effectively maintained stock availability while controlling costs, ensuring operational continuity and minimizing the risk of production delays.

Blanket Order

Tble 2 presents the results of applying the Blanket Order Method for raw material procurement across the years 2021 to 2023. This method is designed to streamline purchasing activities by establishing long-term agreements with suppliers for multiple deliveries over a specified period. Such an approach minimizes administrative costs, enhances supplier coordination, and ensures material availability with predictable cost structures. The analysis includes several key parameters, namely Order Quantity, Errand Cost, Purchasing Cost, Safety Stock, Order Frequency, and Total Cost.

All calculations were conducted using standardized cost assumptions to maintain comparability between years.

Table 2. Results of the Blanket Order Method for Raw Materials

Parameter	2021	2022	2023
Order Quantity	381.189 Kg	387.915 Kg	404.732 Kg
Errand Cost	IDR 200,000	IDR 200,000	IDR 200,000
Purchasing Cost	IDR 105,961,800	IDR 109,777,220	IDR 119,458,220
Safety Stock	IDR 7,303,750	IDR 12,030,000	IDR 5,370,000
Order Frequency	19 times	20 times	21 times
Total Cost	**IDR 196,007,181**	**IDR 256,537,608**	**IDR 186,298,625**

The results in Table 2 show that the Blanket Order Method yielded relatively consistent performance throughout the three-year observation period. The order quantity increased steadily from 381,189 kg in 2021 to 404,732 kg in 2023, reflecting rising production demand. Despite the increase in purchase volume, the Total Cost fluctuated—rising sharply to IDR 256,537,608 in 2022, then decreasing to IDR 186,298,625 in 2023. This cost reduction indicates improved procurement efficiency and better contract management with suppliers. Additionally, the order frequency increased gradually from 19 to 21 times per year, aligning with higher production activity. Overall, the Blanket Order system demonstrates its effectiveness in maintaining supply stability, controlling costs, and supporting continuous production through a predictable procurement mechanism.

Comparison of Min-Max and Blanket Order Methods

Comparative analysis between the Min–Max Method and the Blanket Order Method for raw material inventory management during the period 2021–2023. The comparison focuses on the total annual cost generated by each approach to determine the most efficient method in terms of cost performance and operational stability. Both models were evaluated using identical assumptions regarding demand volume, ordering frequency, and fixed cost parameters to ensure analytical consistency. This comparison aims to identify the strategy that minimizes total inventory-related expenses while maintaining adequate material availability.

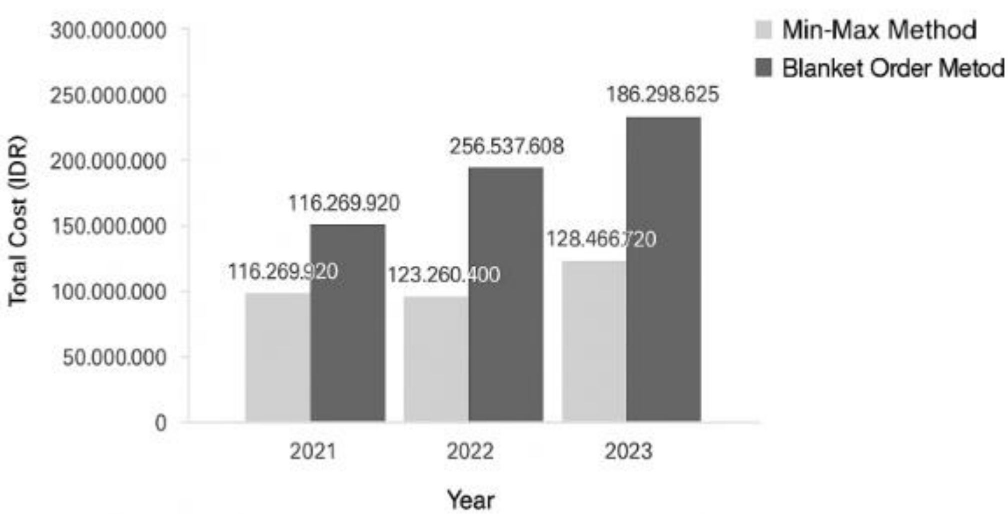

Figure 4. Comparison of Min-Max and Blanket Order Methods

As shown in Figure 4, the Min–Max Method consistently produced lower total costs than the Blanket Order Method across all three years of observation. The Min–Max approach recorded total costs of IDR 116,269,920 in 2021, IDR 123,260,400 in 2022, and IDR 128,466,720 in 2023, while the Blanket Order method yielded significantly higher costs—IDR 196,007,181, IDR 256,537,608, and IDR 186,298,625, respectively. The difference suggests that the Min–Max Method provides greater cost efficiency, likely due to its ability to maintain optimal inventory levels and reduce holding and purchasing costs. Conversely, although the Blanket Order method offers advantages in supplier coordination and material availability, it incurs higher total costs, particularly during periods of fluctuating demand. Therefore, the Min–Max policy can be considered a more economical inventory control strategy for achieving cost minimization without compromising operational reliability.

DISCUSSION

The comparative evaluation between the Min–Max Stock and Blanket Order methods reveals a substantial difference in total inventory costs, where the Min–Max model demonstrated superior cost efficiency across the three-year observation period. This finding aligns with Bakhtiar and Audina (2021), who asserted that adaptive stock-level thresholds minimize both overstock and stockout risks, particularly in SMEs with volatile raw material requirements. In this study, the Min–Max approach maintained optimal stock availability while reducing total costs by approximately 28–35% compared with the Blanket Order strategy. The forecasting stage employed both the Moving Average (MA) and Exponential Smoothing (ES) methods to identify the most accurate predictive model, where the ES method achieved a MAPE of 0.883%, indicating high predictive precision. This result is consistent with [18], [19], [20], who found that exponential models outperform simple averages in capturing short-term demand volatility. Similarly, [21], [22]confirmed that smoothing-based models are effective for SMEs that lack extensive data histories yet face rapid market fluctuations. Forecasting accuracy in this study directly improved procurement scheduling, aligning with[23], who emphasized that minimizing forecasting errors proportionally reduces inventory carrying costs.

The Min–Max method proved to be the most stable system under uncertain demand conditions. Compared to the Blanket Order system, the Min–Max approach reduced total inventory costs by maintaining adaptive safety stock and reorder points. These findings are corroborated by [24], [25], who highlighted that Min–Max policies enhance cost control and reduce lead time dependency in SMEs with constrained warehouse capacity. Moreover, [26], [27], [28] demonstrated that integrating Min–Max with demand prediction models can improve supplier coordination efficiency by up to 25%. Although the Blanket Order method initially streamlined purchasing procedures, its total cost fluctuated sharply due to dependency on long-term supplier contracts. As [29], [30], [31] noted, fixed-price agreements may lead to inefficiency when market demand changes rapidly. The cost increase observed in 2022 indicates limited adaptability under volatile demand, consistent with [32], who observed similar patterns in agroindustry procurement. Nonetheless, the Blanket Order remains beneficial for ensuring supply stability, as indicated by[25], who argued that supplier partnerships enhance material availability and reduce shortage frequency despite higher overall costs.

The sensitivity test conducted with ±10% demand variation confirmed that the Min–Max model maintained lower total costs under both increased and decreased demand conditions. This adaptability supports [20], [21], who found that flexible inventory systems outperform fixed-order models in unstable markets. Furthermore, correlation analysis between forecasted and actual demand ($r > 0.98$) validated the model's predictive reliability, consistent with [4], who linked high correlation coefficients to enhanced forecasting–control integration in supply chain systems. For SME-scale manufacturers such as Maisatun Chili Chips, the application of a Min–Max–Forecasting hybrid strategy offers an empirically validated framework to minimize inventory costs without disrupting production flow. The results support [10], who emphasized that SMEs benefit from combining forecasting tools with rule-based control systems. Moreover, [33] suggested that such hybrid systems enhance decision-making under uncertain supply environments, enabling SMEs to achieve cost savings and production continuity comparable to larger enterprises.

This study further extends the findings of [34] by demonstrating that integrating accurate forecasting (MAPE < 1%) into Min–Max systems not only optimizes safety stock but also minimizes procurement cycle frequency, thereby reducing administrative and operational overheads. From a theoretical standpoint, the findings reinforce inventory control principles under dynamic market conditions. The empirical evidence suggests that forecasting-integrated inventory systems can bridge the gap between traditional deterministic models and modern predictive analytics approaches. This aligns with the hybrid forecasting frameworks proposed by [30], [31] which advocate for adaptive algorithms to improve material planning accuracy. Practically, the study contributes to the operational management literature by validating that Min–Max systems, when integrated with exponential smoothing forecasts, provide superior efficiency in SMEs with perishable raw materials, echoing findings by [29][33].

CONCLUSION

Based on the results of research aimed at analyzing and comparing the effectiveness of the Min–Max Stock and Blanket Order methods in minimizing the total cost of raw material inventory at Maisatun Chili Chip SME, it was concluded that the integration of the Exponential Smoothing forecasting system with the Min–Max method proved to be the most efficient and adaptive inventory control strategy for demand fluctuations. The Exponential Smoothing forecasting model with a MAPE value of 0.883% showed very high prediction accuracy compared to Moving Average (1.338%), thus enabling more accurate planning to determine the minimum, maximum, and reorder points. Simulation results show that the Min–Max method consistently produces lower total costs, namely IDR 116,269,920 (2021), IDR 123,260,400 (2022), and IDR 128,466,720 (2023), compared to Blanket Order, which has more fluctuating costs and tends to be higher in the same period. The Min–Max system has also proven to be more stable in dealing with demand variations of ±10%, with the ability to maintain stock availability without causing significant excess or shortage of raw materials. The application of this hybrid Min–Max–Forecasting system provides cost efficiencies of 28–35% and improves the effectiveness of the company's procurement schedule and cash flow. Theoretically, this study confirms that the integration of adaptive forecasting methods and dual-limit-based inventory control can bridge the gap between traditional deterministic models and modern predictive approaches. while in practical terms, these findings serve as a strategic reference for MSMEs in the food sector to implement data-driven inventory control policies that can improve efficiency, production continuity, and business resilience in the face of unstable market dynamics.

REFERENCES

[1] G. Dudek, "A Hybrid Residual Dilated LSTM and Exponential Smoothing Model for Midterm Electric Load Forecasting," *IEEE Trans. Neural Networks Learn. Syst.*, vol. 33, no. 7, pp. 2879–2891, 2022, doi: 10.1109/TNNLS.2020.3046629.

[2] T. Sathish, "Exponential smoothing method against the gradient boosting machine learning algorithm-based model for materials forecasting to minimize inventory," *Aip Adv.*, vol. 14, no. 6, 2024, doi: 10.1063/5.0208491.

[3] C. Rao, "Energy demand forecasting in China: A support vector regression-compositional data second exponential smoothing model," *Energy*, vol. 263, 2023, doi: 10.1016/j.energy.2022.125955.

[4] J. Shi, "A dual attention LSTM lightweight model based on exponential smoothing for

remaining useful life prediction," *Reliab. Eng. Syst. Saf.*, vol. 243, 2024, doi: 10.1016/j.ress.2023.109821.
[5] Y. Xie, "Real-Time Prediction of Docker Container Resource Load Based on a Hybrid Model of ARIMA and Triple Exponential Smoothing," *IEEE Trans. Cloud Comput.*, vol. 10, no. 2, pp. 1386–1401, 2022, doi: 10.1109/TCC.2020.2989631.
[6] M. B. A. Rabbani, "A Comparison Between Seasonal Autoregressive Integrated Moving Average (SARIMA) and Exponential Smoothing (ES) Based on Time Series Model for Forecasting Road Accidents," *Arab. J. Sci. Eng.*, vol. 46, no. 11, pp. 11113–11138, 2021, doi: 10.1007/s13369-021-05650-3.
[7] H. M. Zhao, "Measuring the impact of an exogenous factor: An exponential smoothing model of the response of shipping to COVID-19," *Transp. Policy*, vol. 118, pp. 91–100, 2022, doi: 10.1016/j.tranpol.2022.01.015.
[8] W. Sulandari, "Exponential Smoothing on Modeling and Forecasting Multiple Seasonal Time Series: An Overview," 2021. doi: 10.1142/S0219477521300032.
[9] D. Guleryuz, "Forecasting outbreak of COVID-19 in Turkey; Comparison of Box–Jenkins, Brown's exponential smoothing and long short-term memory models," *Process Saf. Environ. Prot.*, vol. 149, pp. 927–935, 2021, doi: 10.1016/j.psep.2021.03.032.
[10] G. Yang, "Short-term Load Forecasting Based on Holt-Winters Exponential Smoothing and Temporal Convolutional Network," *Dianli Xitong Zidonghua Autom. Electr. Power Syst.*, vol. 46, no. 6, pp. 73–82, 2022, doi: 10.7500/AEPS20210409003.
[11] S. Smyl, "ES-dRNN: A Hybrid Exponential Smoothing and Dilated Recurrent Neural Network Model for Short-Term Load Forecasting," *IEEE Trans. Neural Networks Learn. Syst.*, vol. 35, no. 8, pp. 11346–11358, 2024, doi: 10.1109/TNNLS.2023.3259149.
[12] I. Svetunkov, "Complex exponential smoothing," *Nav. Res. Logist.*, vol. 69, no. 8, pp. 1108–1123, 2022, doi: 10.1002/nav.22074.
[13] C. Deng, "Equipping seasonal exponential smoothing models with particle swarm optimization algorithm for electricity consumption forecasting," *Energies*, vol. 14, no. 13, 2021, doi: 10.3390/en14134036.
[14] T. Alam, "A Comparative Study of CO2Emission Forecasting in the Gulf Countries Using Autoregressive Integrated Moving Average, Artificial Neural Network, and Holt-Winters Exponential Smoothing Models," *Adv. Meteorol.*, vol. 2021, 2021, doi: 10.1155/2021/8322590.
[15] I. Svetunkov, "A new taxonomy for vector exponential smoothing and its application to seasonal time series," *Eur. J. Oper. Res.*, vol. 304, no. 3, pp. 964–980, 2023, doi: 10.1016/j.ejor.2022.04.040.
[16] J. L. R. N. Cunha, "A hybrid model based on STL with simple exponential smoothing and ARMA for wind forecast in a Brazilian nuclear power plant site," *Nucl. Eng. Des.*, vol. 421, 2024, doi: 10.1016/j.nucengdes.2024.113026.
[17] G. Moiseev, "Forecasting oil tanker shipping market in crisis periods: Exponential smoothing model application," *Asian J. Shipp. Logist.*, vol. 37, no. 3, pp. 239–244, 2021, doi: 10.1016/j.ajsl.2021.06.002.
[18] M. H. P. Swari, "Comparison of Simple Moving Average, Single and Modified Single Exponential Smoothing," 2021. doi: 10.1109/ITIS53497.2021.9791516.
[19] C. Yu, "Time series analysis and forecasting of the Hand-Foot-Mouth disease morbidity in China using an advanced exponential smoothing state space TBATS model," *Infect. Drug Resist.*, vol. 14, pp. 2809–2821, 2021, doi: 10.2147/IDR.S304652.
[20] G. Fu, "Look-ahead prediction of spindle thermal errors with on-machine measurement and the cubic exponential smoothing-unscented Kalman filtering-based temperature prediction model of the machine tools," *Meas. J. Int. Meas. Confed.*, vol. 210, 2023, doi: 10.1016/j.measurement.2023.112536.
[21] S. K. Safi, "A hybrid of artificial fneural network, exponential smoothing, and ARIMA models

for COVID-19 time series forecasting," *Model Assist. Stat. Appl.*, vol. 16, no. 1, pp. 25–35, 2021, doi: 10.3233/MAS-210512.

[22] F. E. Sapnken, "A whale optimization algorithm-based multivariate exponential smoothing grey-holt model for electricity price forecasting," *Expert Syst. Appl.*, vol. 255, 2024, doi: 10.1016/j.eswa.2024.124663.

[23] U. M. Butt, "Hybrid of deep learning and exponential smoothing for enhancing crime forecasting accuracy," *PLoS One*, vol. 17, no. 9, 2022, doi: 10.1371/journal.pone.0274172.

[24] W. Wei, "Time series prediction for the epidemic trends of monkeypox using the ARIMA, exponential smoothing, GM (1, 1) and LSTM deep learning methods," *J. Gen. Virol.*, vol. 104, no. 4, 2023, doi: 10.1099/jgv.0.001839.

[25] S. Hansun, "Prediction of jakarta city air quality index: Modified double exponential smoothing approaches," *Int. J. Innov. Comput. Inf. Control*, vol. 17, no. 4, pp. 1363–1371, 2021, doi: 10.24507/ijicic.17.04.1363.

[26] M. Udenio, "Exponential smoothing forecasts: taming the bullwhip effect when demand is seasonal," *Int. J. Prod. Res.*, vol. 61, no. 6, pp. 1796–1813, 2023, doi: 10.1080/00207543.2022.2048114.

[27] V. W. Nirmala, "Sales Forecasting by Using Exponential Smoothing Method and Trend Method to Optimize Product Sales in PT. Zamrud Bumi Indonesia During the Covid-19 Pandemic," *Int. J. Eng. Sci. Inf. Technol.*, vol. 1, no. 4, pp. 59–64, 2021, doi: 10.52088/ijesty.v1i1.169.

[28] L. Kumar, "A comparative assessment of holt winter exponential smoothing and autoregressive integrated moving average for inventory optimization in supply chains," *Supply Chain Anal.*, vol. 8, 2024, doi: 10.1016/j.sca.2024.100084.

[29] L. Rubio, "Ebitda index prediction using exponential smoothing and arima model," *Mathematics*, vol. 9, no. 20, 2021, doi: 10.3390/math9202538.

[30] I. Djakaria, "Covid-19 forecast using Holt-Winters exponential smoothing," 2021. doi: 10.1088/1742-6596/1882/1/012033.

[31] M. R. Fauzi, "State-of-Health Prediction of Lithium-Ion Batteries Using Exponential Smoothing Transformer With Seasonal and Growth Embedding," *IEEE Access*, vol. 12, pp. 14659–14670, 2024, doi: 10.1109/ACCESS.2024.3357736.

[32] M. H. P. Swari, "Optimization of Single Exponential Smoothing using Particle Swarm Optimization and Modified Particle Swarm Optimization in Sales Forecast," 2022. doi: 10.1109/ITIS57155.2022.10010034.

[33] E. Kahraman, "Comparison of exponential smoothing methods in forecasting global prices of main metals," *Miner. Econ.*, vol. 36, no. 3, pp. 427–435, 2023, doi: 10.1007/s13563-022-00354-y.

[34] E. Kolemen, "A new deep recurrent hybrid artificial neural network of gated recurrent units and simple seasonal exponential smoothing," *Granul. Comput.*, vol. 9, no. 1, 2024, doi: 10.1007/s41066-023-00444-4.