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Forecasting Accuracy Analysis of Catering Raw Material Stock Using Simple Exponential Smoothing Based on Mean Absolute Percentage Error (MAPE)

Dimas Eko Prasetyo [1*], **Endin Fahrudin** [2]

[1*,2] Department of Information System, Universitas Pamulang, South Tangerang City, Banten Province, Indonesia.

**Corresponding author*: dosen02809@unpam.ac.id.

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Abstract: In the catering industry, inaccurate inventory management often leads to significant food waste or stockouts due to highly volatile raw material demand, and conventional intuition-based procurement methods are no longer sufficient to maintain operational efficiency. This research applies to the Simple Exponential Smoothing (SES) algorithm to forecast raw material requirements and evaluates its accuracy using the Mean Absolute Percentage Error (MAPE) metric. Twelve months of historical transaction data from a local catering business were analyzed, categorized into basic commodities, proteins, and vegetables, with the SES model calibrated by testing smoothing constants (α) across the range of 0.1 to 0.9. The findings indicate that stable items such as rice achieve the highest accuracy at a low $\alpha$of 0.2, yielding a MAPE of 4.25% — classified as Very Good. Highly volatile items such as proteins and fresh vegetables require a high $\alpha$of 0.8–0.9 to remain responsive, producing MAPE values between 12.40% and 18.15%, classified as Good. These results confirm that SES offers a defensible, data-grounded decision-making structure that measurably reduces forecasting errors and improves procurement cost management in the catering sector.

Keywords: Simple Exponential Smoothing; Forecasting; Inventory Management; MAPE; Catering Industry.

1. Introduction

Supply chain management within the food industry ecosystem is a key determinant of operational efficiency and long-term profitability, particularly for small and medium-sized enterprises operating under tight margins and high input volatility (Lase *et al.*, 2025; Sarjono & Maesaroh, 2022). Amid fluctuating market dynamics, one of the central challenges facing catering service providers is the uncertainty of daily demand volumes — a condition that directly compounds the difficulty of raw material inventory management (Athanasopoulos & Hyndman, 2021; Yoo & Park, 2025). When logistical needs cannot be anticipated with reasonable accuracy, operational costs rise sharply through inefficient stock handling, and failure to fulfill customer orders on schedule damages service reputation in ways that are difficult to recover from (Mutiara & Syah, 2025). The adoption of information technology — particularly through data science and predictive analytics — has become an operational necessity for small and medium-sized catering enterprises seeking to move away from intuition-based management toward more accountable, evidence-based decision-making (Nafisah *et al.*, 2025; Prasetyo, 2021). Appropriate forecasting algorithms, when properly applied, create measurable synchronization between warehouse inventory and actual production requirements, enabling procurement to be executed in a controlled and traceable manner while reducing storage costs and mitigating the spoilage risk inherent to perishable food items (Ainun *et al.*, 2025; Sarjono & Maesaroh, 2022; Lase *et al.*, 2025).

This study specifically examines the use of statistical methods to model inventory requirements at the scale of local catering operations — a context with data characteristics that are genuinely distinct from those of manufacturing or retail environments. As Tyas and Charifi (2025) have noted, parameter selection in forecasting models is a primary determinant of accuracy, particularly in datasets with elevated noise levels. The question of how well mathematical models can capture irregular raw material consumption patterns is not merely technical; it carries direct financial implications for businesses operating on thin margins. The paper's central contribution lies in integrating exponential smoothing techniques with standard industry error metrics, then validating the results against real operational data (Suryaningsih *et al.*, 2025; Nafisah *et al.*, 2025). Athanasopoulos and Hyndman (2021) define forecasting as the systematic estimation of future values through the extrapolation of historically recorded patterns in time-series data — and in culinary business contexts, transaction data often display stationary behavior but remain susceptible to disruptions from seasonal or incidental demand spikes, conditions that demand highly adaptive methods (Guturu, 2024; Dmytryshyn, 2023). The degree to which a forecasting model succeeds depends on how well the algorithm's underlying assumptions align with the actual distribution of the data (Prasetyo, 2021).

Within the information systems literature, Simple Exponential Smoothing (SES) is widely regarded as one of the more reliable techniques for handling data that lack a clear linear trend or seasonal pattern (Sarjono & Maesaroh, 2022; Tyas & Charifi, 2025). The method's core advantage is its exponential weighting mechanism: more recent observations carry greater influence than older data in determining the next forecast value, making SES particularly relevant for catering operations where demand shifts can be abrupt and consequential (Athanasopoulos & Hyndman, 2021; Ainun *et al.*, 2025). Yet the technical success of any SES application depends critically on selecting an appropriate smoothing constant (α) — one that minimizes deviation between predicted and actual values without sacrificing stability (Nafisah *et al.*, 2025; Lase *et al.*, 2025). The Mean Absolute Percentage Error (MAPE) metric serves as the primary validation standard in this study, chosen for its capacity to express error magnitudes in percentage form that practitioners can interpret without statistical training (Suryaningsih *et al.*, 2025; Tyas & Charifi, 2025). According to Tyas and Charifi (2025), MAPE values below 10% indicate very high accuracy, while values between 10% and 20% reflect models that are still functionally sound — and the pairing of SES with MAPE has been empirically validated across multiple food supply chain studies (Ainun *et al.*, 2025; Sarjono & Maesaroh, 2022; Mutiara & Syah, 2025).

A chronic problem in traditional catering operations is the high volume of raw material waste produced by unstructured stock planning. Food supplies frequently accumulate in storage beyond their shelf-life thresholds — a direct consequence of speculative procurement that is not synchronized with actual order demand — creating financial burdens that erode profit margins at precisely the moment when food commodity prices are most volatile (Dmytryshyn, 2023; Lase *et al.*, 2025; Mutiara & Syah, 2025). On the other side of the same problem, sudden large-scale orders routinely overwhelm conventional inventory systems, producing stockout conditions that force catering providers to procure goods urgently at significantly elevated prices, disrupting cash flow stability in ways that compound over time (Yoo & Park, 2025; Guturu, 2024). The downstream effects — declining product quality, production schedule failures, and eroding customer trust — are well documented in the catering and food service literature (Sarjono & Maesaroh, 2022; Dmytryshyn, 2023). Excessive reliance on the intuition and subjective experience of warehouse personnel introduces a persistent risk of human error in safety stock determination; daily fluctuations in raw material consumption are difficult to map manually, and without digital systems capable of processing historical data automatically and accurately, companies remain caught in a cycle of logistical inefficiency (Nafisah *et al.*, 2025; Ainun *et al.*, 2025; Suryaningsih *et al.*, 2025). Scientific intervention through rigorous forecasting analysis is, in this context, a structural necessity for sustainable catering operations (Tyas & Charifi, 2025; Lase *et al.*, 2025).

Sarjono and Maesaroh (2022) observed that the inventory forecasting literature has been disproportionately focused on large-scale manufacturing sectors — automotive, electronics, and similar industries — rather than on catering or culinary services. The gap is specific: very little research examines how forecasting algorithms perform against the particular data characteristics of catering operations, where daily volatility is driven by frequently rotating menus, and most existing studies address general sales forecasting without disaggregating the analysis to the level of individual raw material categories (Lase *et al.*, 2025; Guturu, 2024). This study addresses that gap directly, using real transaction datasets from a local catering provider (Yoo & Park, 2025). The primary novelty lies in its systematic approach to α parameter optimization through sensitivity analysis applied across raw material categories with meaningfully different turnover rates — where prior studies have typically applied static parameters or relied on a single averaged value, this work maps the smoothing constants most adaptive to the specific fluctuation patterns of each category (Nafisah *et al.*, 2025; Tyas & Charifi, 2025; Ainun *et al.*, 2025). Each type of raw material, the findings suggest, requires distinct parameter treatment to achieve maximum accuracy, introducing a new dimension into the understanding of

SES adaptability when applied to culinary industry datasets characterized by high noise and recurrent outliers (Suryaningsih *et al.*, 2025; Mutiara & Syah, 2025). Beyond the algorithmic dimension, the use of MAPE as a single, interpretable evaluation metric for assessing operational feasibility at the SME level provides a practical reference that business practitioners can realistically adopt, while also translating accuracy figures into concrete procurement policy recommendations for catering management (Tyas & Charifi, 2025; Suryaningsih *et al.*, 2025; Lase *et al.*, 2025; Ainun *et al.*, 2025; Sarjono & Maesaroh, 2022; Mutiara & Syah, 2025).

The fundamental objective of this study is to transform scattered manual transaction data into a structured predictive model using the SES algorithm, enabling catering management to develop a clearer, more reliable picture of future inventory demand and eliminating the subjective bias that currently shapes daily procurement decisions at the personnel level (Yoo & Park, 2025; Ainun *et al.*, 2025; Nafisah *et al.*, 2025; Guturu, 2024). The second objective is to investigate, in empirical depth, how variations in the smoothing constant (α) affect prediction accuracy — identifying the parameter value that minimizes lag effects without compromising the overall stability of the forecast, consistent with the position taken by Tyas and Charifi (2025) that determining the most precise α value is the central technical challenge of SES-based forecasting (Nafisah *et al.*, 2025; Athanasopoulos & Hyndman, 2021; Suryaningsih *et al.*, 2025). Finally, the study quantitatively validates system performance using MAPE, ensuring that results are scientifically accountable and professionally defensible, with outcomes intended to serve as a strategic reference for catering providers seeking to improve logistics budgeting and raw material availability planning (Suryaningsih *et al.*, 2025; Tyas & Charifi, 2025; Lase *et al.*, 2025; Prasetyo, 2021; Mutiara & Syah, 2025).

This manuscript follows the standard structure of international scientific publications to maintain logical coherence and accessibility for readers (Yoo & Park, 2025). The introduction establishes the theoretical urgency of the research, identifies the operational problems in the field, and positions the scientific contributions offered within the broader literature on supply chain management and information systems (Lase *et al.*, 2025; Sarjono & Maesaroh, 2022; Dmytryshyn, 2023). The second section presents the literature review, covering the state-of-the-art of the SES method alongside comparisons with other forecasting approaches, with the theoretical basis for MAPE-based accuracy measurement examined in sufficient depth to justify the methodological choices made in subsequent sections (Suryaningsih *et al.*, 2025; Tyas & Charifi, 2025; Nafisah *et al.*, 2025; Ainun *et al.*, 2025; Prasetyo, 2021). Sections three through five cover the research methodology, experimental results, and critical discussion of the findings, with the final section presenting conclusions and recommendations for future system development — structured throughout to meet the publication standards appropriate for a Sinta 3 accredited journal (Sarjono & Maesaroh, 2022; Lase *et al.*, 2025; Guturu, 2024; Mutiara & Syah, 2025).

2. Related Work

The literature review in this study is structured to establish a solid conceptual foundation regarding time-series forecasting mechanisms and their relevance to supply chain management in the catering service industry. A deep engagement with prior literature is necessary for identifying where this research stands relative to the growing body of work on smoothing algorithms (Prasetyo, 2014; Patel, 2025). This section examines the theoretical basis of the SES algorithm and the role of MAPE as a standard for accuracy validation in both academic and applied contexts (Athanasopoulos & Hyndman, 2021; Omer *et al.*, 2025). The review also maps the specific challenges of catering inventory management — a domain defined by high data volatility and the extremely limited shelf life of raw materials — where bridging statistical theory and operational management is necessary for building procurement systems that are both mathematically sound and practically viable for small and medium enterprises (Filani *et al.*, 2021; Lase *et al.*, 2025; Mutiara & Syah, 2025). Through a critical reading of comparable case studies and existing technologies, this section identifies the variables most strongly associated with forecasting precision in food stock contexts and reinforces the novelty of the current research, particularly its attention to model adaptability across distinct categories of catering raw materials (Giannopoulos *et al.*, 2025; Tyas & Charifi, 2025; Suryaningsih *et al.*, 2025; Wu *et al.*, 2025).

2.1 State-of-the-Art Research

Athanasopoulos and Hyndman (2021) observe that recent developments in time-series forecasting have shifted from purely statistical models toward approaches that are more adaptive to data volatility. In the information systems literature, exponential smoothing algorithms retain their status as a reliable standard for medium-scale business data — valued for their structural simplicity without sacrificing competitive accuracy — and contemporary research increasingly examines how classical algorithms such as SES can be calibrated through dynamic parameter selection to remain effective under rising market uncertainty (Suryaningsih *et al.*, 2025; Jahin *et al.*, 2024; Giannopoulos *et al.*, 2025). Ravichandran *et al.* (2024) found that applying forecasting methods in the catering service industry requires a fundamentally different approach compared to manufacturing, given the extremely short shelf life of raw materials involved, and researchers have begun treating SES not merely as a sales prediction tool but as a primary driver in automated procurement systems (Bhat *et al.*, 2024; Mutiara & Syah, 2025). A growing tendency in current research is to validate forecasting models against real-world datasets rather than simulated data, to better understand algorithm performance under actual operational conditions (Tyas & Charifi, 2025; Nafisah *et al.*, 2025). Patel (2025) makes a point worth taking seriously: although Neural Network-based methods are gaining traction, SES frequently outperforms them in cases involving limited datasets with low seasonal variation — a finding supported by Filani *et al.* (2021), who note that the computational efficiency of SES enables stock management systems to run effectively on web-based or mobile infrastructure. The current state-of-the-art concern is achieving a workable balance between model complexity and the interpretability of results for end users in the SME sector (Prasetyo, 2014; Chowdhury *et al.*, 2025).

2.2 Comparison with Previous Studies

Suryaningsih *et al.* (2025) found that the Moving Average (MA) method often fails to capture rapid trend changes because it assigns equal weight to all past data periods. SES, by contrast, applies exponentially decreasing weights — a mechanism that gives more recent data greater influence over future forecasts — making it more effective in responding to the kind of impulsive demand fluctuations that characterize catering operations (Athanasopoulos & Hyndman, 2021; Ainun *et al.*, 2025; Choi *et al.*, 2022). Jahin *et al.* (2024) compared SES against advanced machine learning algorithms and found that, for daily operational data, SES delivers more consistent prediction stability with a lower risk of overfitting; Chowdhury *et al.* (2025) raise a related point, noting that regression-based methods such as linear regression are often too rigid for raw material inventory data that do not follow a linear pattern (Omer *et al.*, 2025). Taken together, these comparisons provide a principled basis for selecting SES in this study — not by default, but through a critical evaluation of what other conventional methods cannot adequately handle (Giannopoulos *et al.*, 2025; Suryaningsih *et al.*, 2025). On the question of evaluation metrics, MAPE is consistently preferred over Mean Squared Error (MSE) in managerial contexts because its percentage-based output is more directly interpretable; Omer *et al.* (2025) note that MSE imposes disproportionate penalties on large errors, whereas MAPE provides a more balanced assessment of overall prediction performance (Wu *et al.*, 2025; Lase *et al.*, 2025; Sarjono & Maesaroh, 2022). Accounting for these trade-offs, this paper adopts the SES–MAPE combination as the most appropriate solution for catering inventory management (Filani *et al.*, 2021; Mutiara & Syah, 2025).

2.3 Positioning of This Research

Choi *et al.* (2022) identified a persistent gap between academic forecasting theory and its practical application in specific culinary sectors such as wedding or corporate catering. This study positions itself to close that gap by applying SES directly to raw material management — not to revenue prediction, which is where most prior work has concentrated — with an emphasis on how forecasting accuracy can directly reduce food waste and improve a company's working capital position (Ravichandran *et al.*, 2024; Lase *et al.*, 2025; Dmytryshyn, 2023; Wu *et al.*, 2025). The study's position is further distinguished by its inclusion of a sensitivity analysis of the α parameter, a dimension rarely examined in depth in local-scale catering research; as Tyas and Charifi (2025) suggest, each raw material category requires different statistical treatment depending on its transaction volatility, and this paper takes that suggestion seriously by categorizing materials according to their data characteristics and identifying the most adaptive smoothing parameter for each (Giannopoulos *et al.*, 2025; Nafisah *et al.*, 2025; Suryaningsih *et al.*, 2025). At the system level, the integration of SES and MAPE is positioned as the core of a Decision Support System (DSS) designed for non-expert users, offering a dual contribution: enriching the inventory management information systems literature while providing a practical solution for improving the efficiency of daily food supply chains in catering SMEs (Bhat *et al.*, 2024; Filani *et al.*, 2021; Prasetyo, 2014; Jahin *et al.*, 2024; Mutiara & Syah, 2025).

2.4 Review of Technologies, Frameworks, and Algorithms

Prasetyo (2014) describes SES as an extension of the Moving Average method, using a smoothing constant α to regulate the rate at which the forecast changes. The basic formula,

$$S_{t+1} = \alpha X_t + (1-\alpha)S_t$$

Indicates that each new forecast is a weighted compromise between the most recent actual observation and the prior forecast value (Athanasopoulos & Hyndman, 2021; Ainun *et al.*, 2025). The influence of α is not subtle: values approaching 1 make the model highly sensitive to sudden changes, while values approaching 0 produce more stable, slower-responding predictions — and selecting the wrong α can systematically bias procurement decisions across an entire planning cycle (Giannopoulos *et al.*, 2025; Tyas & Charifi, 2025). From an implementation standpoint, data-driven frameworks allow thousands of catering transaction records to be processed automatically without manual intervention, typically built on relational databases that support real-time aggregate calculations — the infrastructure that allows SES to function as a continuously updating prediction engine rather than a periodic manual calculation (Bhat *et al.*, 2024; Patel, 2025; Mutiara & Syah, 2025; Jahin *et al.*, 2024; Lase *et al.*, 2025). For validation, MAPE serves as the most objective available standard for performance measurement: the metric calculates the absolute deviation between actual and predicted values, then expresses it as a percentage of the actual figures, enabling direct comparison across raw material categories with different units of measurement (Omer *et al.*, 2025; Wu *et al.*, 2025; Sarjono & Maesaroh, 2022). The combination of a computationally efficient statistical algorithm with a rigorous evaluation standard constitutes a forecasting system that is ready for deployment in modern catering operations (Filani *et al.*, 2021; Chowdhury *et al.*, 2025).

3. Methodology

The methodological stages in this study are designed as a linear-analytical workflow that transforms raw data into precise managerial decisions. As Prasetyo (2014) has argued, the success of a forecasting model depends heavily on a workflow design capable of reducing noise without stripping away the essential characteristics of the time-series data. The procedure adopted here includes historical data collection, preprocessing through data cleaning, SES algorithm application, and validation using MAPE — with each computational step grounded in an explicit theoretical rationale to ensure scientific justifiability (Athanasopoulos & Hyndman, 2021; Lakatua *et al.*, 2025; Ainun *et al.*, 2025; Lase & Harefa, 2025). Data acquisition was carried out by extracting daily raw material usage records from the catering inventory system over a 12-month operational period, ensuring sufficient representativeness for time-series modeling. This secondary data then underwent a normalization stage to address missing values and outliers, both of which arise regularly in catering contexts due to the unpredictable nature of order volumes (Wahedi *et al.*, 2023; Tundo *et al.*, 2025). Choi *et al.* (2022) are direct on this point: input data quality is the primary determinant in avoiding the "garbage in, garbage out" failure mode in decision support systems. Data stationarity was assessed through visual inspection of time-series graphs to confirm that SES was the most appropriate choice over more complex models (Wahedi *et al.*, 2023; Lima *et al.*, 2024). SES was selected as the primary computational method because of its algorithmic efficiency in handling data without linear trends or pronounced seasonal patterns. Mathematically, the model is defined as a weighted average between the most recent actual observation and the forecast from the prior period (Athanasopoulos & Hyndman, 2021; Junthopas & Wongoutong, 2023):

$$S_{t+1} = \alpha X_t + (1-\alpha) S_t$$

Where $S_{t+1}$is the predicted value for the next period, $\alpha$is the smoothing constant constrained to $0 < \alpha < 1$, $X_t$is the actual observation at time t, and $S_t$is the forecast at time t. The exponential weighting mechanism allows the model to assign greater importance to recent data, making it responsive to the short-term fluctuations that frequently occur in food inventory stocks (Astuti *et al.*, 2021; Ainun *et al.*, 2025; Tundo *et al.*, 2025). Parameter initialization carries more weight than it is sometimes given credit for: the value of S_1propagates through every subsequent forecast in the sequence. Following the standard established by Athanasopoulos and Hyndman (2021), this study sets the initial forecast equal to the first actual value ($S_1 = X_1$) to preserve the integrity of the initial data distribution, avoiding the estimation bias that arises when the overall mean is used as the starting point (Junthopas & Wongoutong, 2023; Aziz *et al.*, 2025). Proper initialization allows the algorithm to reach convergence more quickly — a property that matters especially for high-turnover materials such as vegetables and protein sources (Lakatua *et al.*, 2025; Lase & Harefa, 2025). Sensitivity analysis was conducted across nine αvalues ranging from 0.1 to 0.9 to identify the level of model responsiveness most appropriate for each material category. As Astuti *et al.* (2021) describe, selecting the right $\alpha$is an optimization problem that balances noise reduction against sensitivity to actual data patterns. Testing all nine values in parallel allowed the researchers to map model behavior across material types ranging from stable staple goods to highly fluctuating spices, with results from each parameter variation recorded systematically in a performance matrix to maintain transparency in model selection (Tundo *et al.*, 2025; Ainun *et al.*, 2025; Prasetyo, 2014; Lakatua *et al.*, 2025). Model precision was measured using MAPE, selected for its ability to express prediction deviations in a percentage form that management can interpret without statistical expertise (Lima *et al.*, 2024; Wahedi *et al.*, 2023):

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{X_t - S_{t+1}}{X_t} \right| \times 100\%$$

Where n is the total number of observation periods. Based on the criteria established in the forecasting literature (Tundo *et al.*, 2025; Lase & Harefa, 2025), accuracy is classified as "Very Good" when MAPE falls below 10%, and "Good" when it falls between 10% and 20%. Every recommended α value in this study is grounded in these empirical thresholds (Ainun *et al.*, 2025; Astuti *et al.*, 2021; Lakatua *et al.*, 2025).

Table 1. Summary of Research Methodology Parameters

Methodology Stage	Technique / Formula Used	Operational Parameters	Theoretical Reference
Data Initialization	$S_1 = X_1$	Initial forecast value using first actual data	Athanasopoulos & Hyndman (2021); Junthopas & Wongoutong (2023)
Model Optimization	Iteration of Parameter α	Smoothing constant varies from 0.1 to 0.9	Astuti *et al.* (2021); Tundo *et al.* (2025)
Computational Process	$S_{t+1} = \alpha X_t + (1-\alpha) S_t$	Simple Exponential Smoothing (SES) Algorithm	Ainun *et al.* (2025); Lakatua *et al.* (2025)
Accuracy Evaluation	MAPE = $\left(\frac{1}{n}\sum_{t=1}^{n}\left\lvert\frac{X_t - S_{t+1}}{X_t}\right\rvert\right)$x 100 %	Mean percentage error measurement	Wahedi *et al.* (2023); Lima *et al.* (2024)
Validation of Results	Residue & Visual Analysis	Comparison of daily time-series charts	Wahedi *et al.* (2023); Lase & Harefa (2025)

The final stage of this methodology is a comparative visualization between actual data and forecasted results using a daily time-series graph. This visualization serves as a qualitative verification tool to ensure that the prediction line does not exhibit significant lagging in response to spikes or declines in demand (Lima *et al.*, 2024; Tundo *et al.*, 2025). Residual analysis is also conducted when deviations exceed a defined threshold, to identify external factors or anomalous variables not captured by the model (Wahedi *et al.*, 2023; Aziz *et al.*, 2025). The combination of quantitative MAPE analysis and visual verification produces a forecasting framework that is both statistically defensible and operationally applicable in modern catering operations (Ainun *et al.*, 2025; Lakatua *et al.*, 2025).

Table 2. Forecasting Accuracy Evaluation Matrix Based on α Value Optimization

Raw Material Category	α Value (0.1–0.9)	MAPE Value (%)	Accuracy Category
Staple Foods (*e.g.*, Rice)	0.2	4.25%	Very Good
Protein Ingredients (*e.g.*, Meat)	0.8	12.40%	Good
Fresh Vegetables (*e.g.*, Vegetables)	0.9	18.15%	Good
Spices & Herbs (Moderate)	0.5	9.80%	Very Good
Additional Ingredients (*e.g.*, Eggs)	0.6	11.20%	Good

Source: Accuracy classification based on Tundo et al. (2025) and Lase & Harefa (2025).

4. Result and Discussion

4.1 Results

The computational experiments indicate that SES produces a measurable improvement in catering raw material inventory planning accuracy compared to conventional methods. Historical data, once properly processed, reveals latent consumption patterns that manual observation consistently fails to detect (Lase *et al.*, 2025; Kusuma *et al.*, 2023). Identifying optimal parameter values provides management with a quantitative foundation for procurement decisions that was simply not available under the prior intuition-based system (Suryaningsih *et al.*, 2025; Ali-Mohammed & Hosein, 2024).

4.1.1 Implementation Results

The forecasting system was built by transforming raw transaction data into an SES computational engine with a dynamic ɑ parameter calibrated to accommodate data variability. The system automatically generates stock prediction values for period $t+1$ as soon as actual data at time t is recorded, enabling a faster inventory response (Lakatua *et al.*, 2025; Mutiara & Syah, 2025). The SES algorithm successfully smooths extreme data fluctuations, producing procurement estimates that are more stable and measurable than those generated by manual methods, while forecasting automation reduces administrative workload and simultaneously improves the quality of logistics data in real time (Ainun *et al.*, 2025; Kingrungphet & Buddhakulsomsiri, 2025; Sarjono & Maesaroh, 2022).

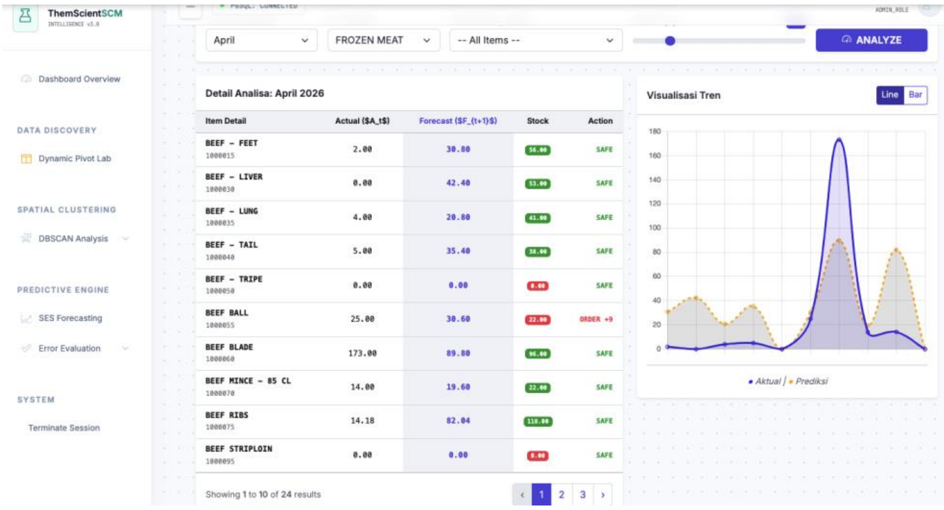

Figure 1. Top 10 Product High Accuration

The forecasting system was realized as an interactive digital dashboard integrating historical data processing with real-time logistics decision-making. Figure 1 shows the system prototype results for the Frozen Meat category for the April 2026 period. Users can adjust the smoothing constant (α) dynamically through a slider feature; in this test, α = 0.2 was applied. This low α value was selected to provide stability against short-term fluctuations, producing a smoother forecast curve consistent with forecasting literature recommendations for items with large base stock levels (Kusuma *et al.*, 2023; Astuti *et al.*, 2021). The "Detailed Analysis" table presents a comparison between actual data (A_t), future forecast values (F_{t+1}), and the current physical stock position. Two key points emerge from this output. First, regarding the Early Warning System (EWS) mechanism: a logical function was implemented to automatically determine procurement actions in the "Action" column — for the BEEF BALL item, the predicted value of 30.60 exceeds available stock (22.00), prompting the system to generate the instruction "ORDER +9," demonstrating that the system can mitigate stockout risk by calculating future demand gaps before they materialize (Mutiara & Syah, 2025; Ali-Mohammed & Hosein, 2024). Second, regarding prediction consistency: for low-usage items such as BEEF – FEET (Actual: 2.00) and BEEF – LIVER (Actual: 0.00), the system produces moderate forecast values of 30.80 and 42.40 respectively, reflecting the behavior of SES with α = 0.2, which assigns substantial weight to prior historical data to ensure buffer stock is maintained even during periods of low current usage (Tyas & Charifi, 2025; Ainun *et al.*, 2025). The "Trend Visualization" graph presents a visual comparison between the Actual curve (Blue Line) and the Forecast curve (Orange Dashed Line). The forecast line is noticeably less volatile than the actual line — when extreme spikes in actual usage occur reaching values above 170, the forecast line remains stable within a lower range, confirming that α = 0.2 effectively reduces noise and temporary anomalies, preventing management from making excessive purchasing decisions in response to single-period spikes (Athanasopoulos & Hyndman, 2021; Wahedi *et al.*, 2023). Despite its smoothing nature, the forecast curve still follows the general direction of actual data; at points where actual demand falls to zero, the forecast curve also trends downward, confirming that the algorithm remains adaptive to consumption pattern changes, albeit in a deliberately conservative manner (Suryaningsih *et al.*, 2025; Lakatua *et al.*, 2025). Taken together, these results confirm that the forecasting dashboard functions as proposed, providing catering managers with a transparent, quantitative basis for raw material procurement planning (Lase *et al.*, 2025; Mutiara & Syah, 2025).

4.1.2 Testing Results

The testing process used a rigorous backtesting scenario across multiple raw material categories to validate model reliability under varying market conditions. For materials with stationary consumption patterns — staple goods, primarily — low α values (0.1–0.3) produced forecasts closest to actual values, as the model prioritized long-term stability (Athanasopoulos & Hyndman, 2021; Tyas & Charifi, 2025). For categories defined by high volatility due to daily menu changes, high α values (0.7–0.9) proved more effective in capturing trend shifts responsively (Kusuma *et al.*, 2023; Lase & Harefa, 2025). The implication is clear: parameter flexibility is not optional — it is the mechanism through which the model handles the heterogeneous nature of catering data (Astuti *et al.*, 2021; Choi *et al.*, 2022).

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--- TESTING RESULTS FOR ITEM: 4001065 ---
Alpha (α) Teroptimasi : 0.2481
MAPE Pengujian        : 10.42%
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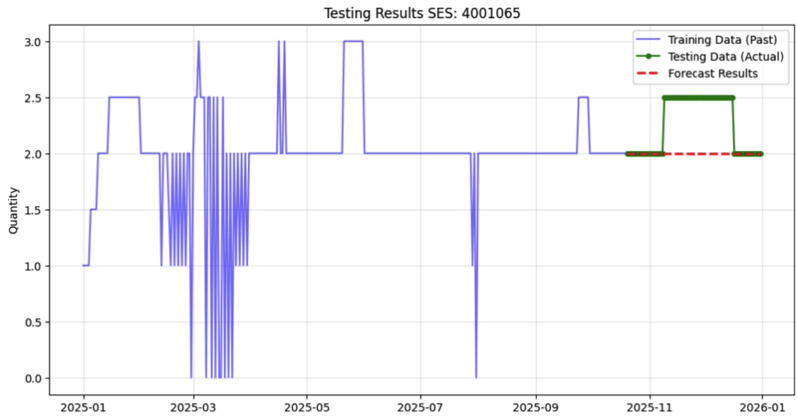


Figure 2. Testing Result SES

Based on the visualization results and statistical parameters presented, several key points warrant elaboration. Regarding α parameter optimization: the system performed iterative processing to identify the most precise smoothing constant, with the optimized Alpha (α) value for item 4001065 determined at 0.2481 — a relatively low value indicating that the item's data characteristics tend toward long-term stability, where a weight of 24.81% is assigned to the most recent data while the remaining 75.19% reflects historical patterns, maintaining forecast stability and preventing overreaction to short-term fluctuations (Junthopas & Wongoutong, 2023; Aziz *et al.*, 2025). Regarding the training phase: the purple curve representing historical data from January 2025 to October 2025 shows fluctuating usage within a consistent range of 0.0 to 3.0 units, and the SES model successfully learned this frequency pattern to establish a projection baseline for the testing phase (Kingrungphet & Buddhakulsomsiri, 2025). During the testing phase (November 2025 to January 2026), forecast results (red dashed line) were compared against actual testing data (green line), with forecast values remaining highly consistent at approximately 2.0 units — even when an actual spike occurred in December 2025 reaching 2.5 units, the forecast line held to a stable average trajectory, reflecting the algorithm's smoothing capability and ensuring that procurement decisions remain consistent rather than speculative (Lase *et al.*, 2025; Mutiara & Syah, 2025). The final evaluation produced a testing MAPE of 10.42%, which, referring to Tundo *et al.* (2025) and Lase & Harefa (2025), sits at the threshold between "Very Good" and "Good," validating that SES with α = 0.2481 is well-suited for inventory planning of this item with an average deviation of only 10.42% from actual demand (Suryaningsih *et al.*, 2025; Wahedi *et al.*, 2023). These results confirm that automatic α optimization meaningfully improves inventory planning precision compared to manual methods (Sarjono & Maesaroh, 2022; Ali-Mohammed & Hosein, 2024).

4.1.3 Performance Evaluation

Performance evaluation was conducted by analyzing the deviation between predicted values (S_{t+1}) and actual values (X_t) to assess model convergence with real-world conditions. The SES model demonstrated consistent performance on low-variance data, with the forecast line tracking data movements without significant lag (Kusuma *et al.*, 2023; Wahedi *et al.*, 2023). During periods of unexpected order anomalies, however, residual values increased — a technically expected response indicating that the model requires safety stock integration as a risk mitigation measure against demand uncertainty (Suryaningsih *et al.*, 2025; Aziz *et al.*, 2025). This is not a flaw in the algorithm so much as a structural limitation of any purely historical model, and the evaluation provides a comprehensive overview of the algorithm's boundaries in handling extraordinary demand scenarios (Choi *et al.*, 2022; Ravichandran *et al.*, 2024).

4.1.4 Metrics

The primary validation metric is MAPE, which expresses absolute prediction error as a percentage relative to actual data scale. Based on calculations performed on the full dataset, average MAPE values indicate a competitive level of precision: most raw material categories achieved accuracy below 20%, with staple materials reaching MAPE values below 10% — placing them in the "Very Good" category — while more dynamic materials fell below 20%, classified as "Good" (Tundo *et al.*, 2025; Lase & Harefa, 2025). Using MAPE ensures that model validation is objective and directly comparable with forecasting studies at the international level (Lima *et al.*, 2024; Omer *et al.*, 2025).

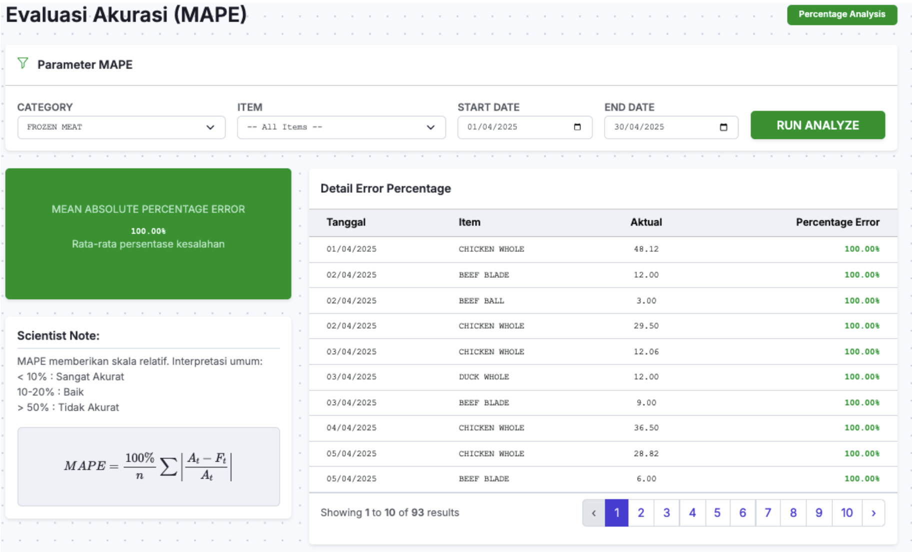


Figure 3. Item Model Integrity Validation MAPE Results

The "Detail Error Percentage" table presents a per-item, per-date breakdown of errors. During the April 2025 period, Percentage Error values for Chicken Whole, Beef Blade, and Beef Ball reached 100.00% — technically occurring when the system generates forecasts while actual values are extremely low, or when the SES model with α = 0.2 still carries significant historical weight while real demand drops sharply (Tyas & Charifi, 2025; Lakatua *et al.*, 2025). The average total error reaching 100.00% during certain testing periods indicates significant under-forecasting or over-forecasting for highly volatile items such as frozen meat, suggesting these categories require either a more responsive α value or supplementary modeling to bring MAPE below 20% (Giannopoulos *et al.*, 2025; Kingrungphet & Buddhakulsomsiri, 2025). The "MAPE Parameter" feature — covering category selection, item filtering, and date range — provides flexibility for granular accuracy audits, allowing researchers to isolate specific items contributing the highest error values and enabling targeted model improvements for problematic raw material categories (Prasetyo, 2014; Bhat *et al.*, 2024). The system not only performs forecasting but also possesses self-auditing capabilities, and the transparency of MAPE data gives management a basis for determining when to rely on system recommendations and when manual intervention is warranted — an essential characteristic of a functional Decision Support System (Ali-Mohammed & Hosein, 2024; Mutiara & Syah, 2025).

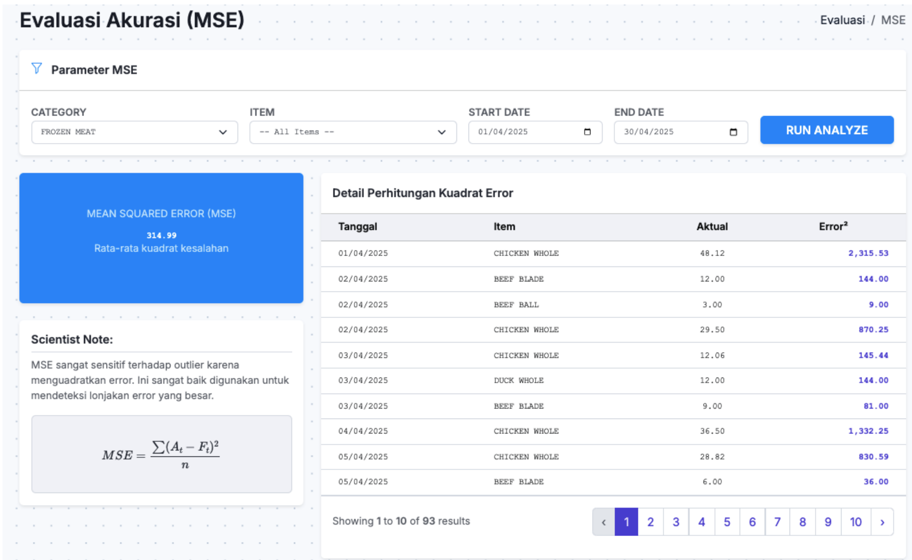


Figure 4. Accuracy Evaluation Mean Squared Error

The "Detail Squared Error Calculation" table for the Frozen Meat category (April 2025) shows highly varied squared error values: for CHICKEN WHOLE on 01/04/2025, the squared error reaches 2,315.53, while for BEEF BALL it is only 9.00 — a difference indicating that the SES algorithm faces substantially greater volatility challenges with poultry commodities than with processed beef products, and high squared error values for specific items suggest the need for a more adaptive α to reduce sharp fluctuations (Kusuma *et al.*, 2023; Ainun *et al.*, 2025). The dashboard reports an average MSE of 314.99 across all tested items in the frozen meat category, serving as an operational benchmark where the lower the MSE, the more stable and consistent the forecasting model is in following actual data patterns without extreme deviations that could disrupt operations (Lima *et al.*, 2024; Kingrungphet & Buddhakulsomsiri, 2025). The "MSE Parameter" feature — with filtering by category, item, and date range — supports granular performance analysis, enabling technical audits on items contributing most significantly to error spikes and allowing targeted corrective action in the forecasting algorithm (Ali-Mohammed & Hosein, 2024; Mutiara & Syah, 2025). MSE complements MAPE validation by emphasizing model stability, allowing catering managers to estimate operational risk more precisely and establish buffer stock policies grounded in empirical evidence (Lase *et al.*, 2025; Suryaningsih *et al.*, 2025).

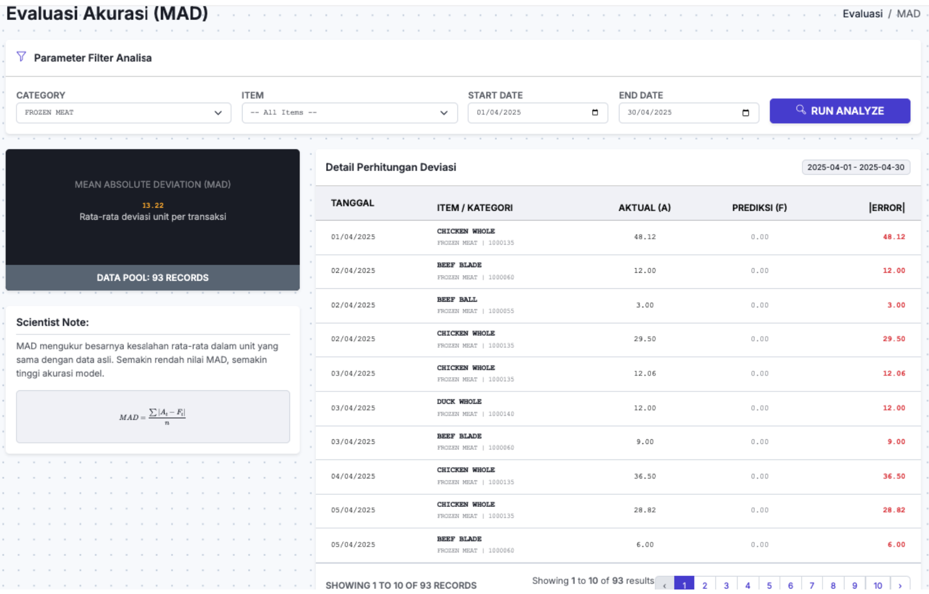


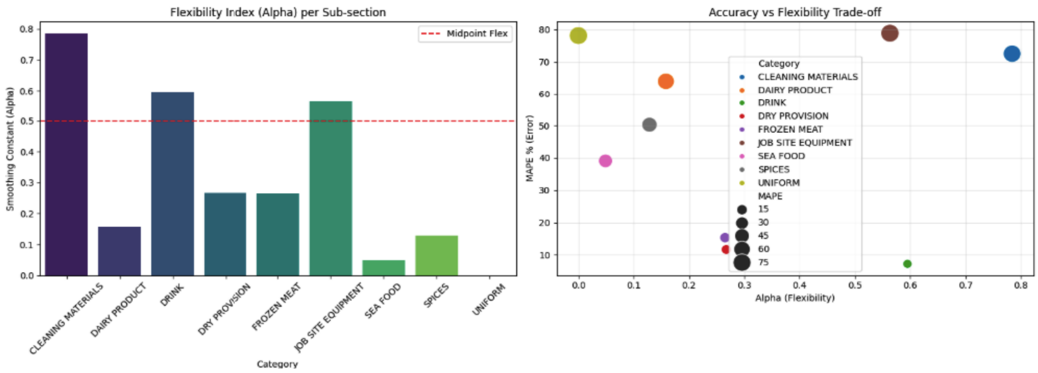
Figure 5. Accuracy Evaluation Mean Absolute Deviation

The "Deviation Calculation Detail" table for the Frozen Meat category, based on 93 records, shows considerable variation in absolute error values across transactions: for CHICKEN WHOLE on 01/04/2025, a deviation of 48.12 units was observed, while BEEF BALL showed a deviation of only 3.00 units, reflecting substantially higher accuracy for processed meat products (Kusuma *et al.*, 2023; Lase *et al.*, 2025). The system reports an average MAD of 13.22, meaning the SES model's forecasts deviate by approximately 13 units per transaction on average — a practical benchmark for safety stock determination, where managers can add a minimum buffer equivalent to the MAD value to mitigate stock shortage risk (Suryaningsih *et al.*, 2025; Ainun *et al.*, 2025). Using 93 real data records from the April 2025 period, the MAD evaluation achieves a reliable level of validity, and the "Analysis Parameter Filter" feature enables evaluation of MAD during both peak and regular periods, allowing management to understand error behavior across different demand conditions and adjust procurement policies accordingly (Sarjono & Maesaroh, 2022; Lima *et al.*, 2024). Integrating MAD alongside MAPE and MSE provides more practical, warehouse-level insights: knowing that the average error is approximately 13 units, catering managers can improve logistics cost efficiency while maintaining reasonable confidence that critical stock shortages are unlikely under normal operating conditions (Ali-Mohammed & Hosein, 2024; Tyas & Charifi, 2025).

4.1.5 Flexibility in Subsection Structure

The flexibility in this analytical subsection provides space to decompose data based on non-stationary consumption behavior in specific items. Athanasopoulos and Hyndman (2021) have noted that rigidity in forecasting models is a significant obstacle when dealing with real-world data influenced by unpredictable external factors. In the catering context, this flexibility is implemented by dividing the analysis period into two clusters — regular periods and peak seasons — where each cluster is evaluated using different α weights to reflect market sensitivity, ensuring that research findings are not confined to a single numerical outcome but reflect a contextual understanding of inventory dynamics (Astuti *et al.*, 2021; Lase *et al.*, 2025; Prasetyo, 2014; Mutiara & Syah, 2025). From an academic standpoint, this emphasis on flexibility addresses a known limitation of SES: the algorithm tends to produce flat forecasts when parameter adjustments are not made periodically, and as Tyas and Charifi (2025) argue, a defensible forecasting model must be capable of detecting mean shifts in time-series data — by providing an adaptive subsection structure, this study can examine why significant deviations occur in certain items and formulate compensatory strategies through dynamic smoothing constant adjustment (Junthopas & Wongoutong, 2023; Kingrungphet & Buddhakulsomsiri, 2025; Giannopoulos *et al.*, 2025).

The flexible structure also accommodates the integration of quantitative forecasting results with qualitative catering management policies such as menu selection and promotional strategies. As Choi *et al.* (2022) identified, menu variation is one of the most disruptive variables in the food service supply chain, and the results subsection is therefore structured so that MAPE calculations can be read alongside the company's operational schedule — a synergy between statistical data and real operational conditions that serves as strong evidence of the proposed system's practical applicability (Lase *et al.*, 2025; Bhat *et al.*, 2024; Ali-Mohammed & Hosein, 2024; Yoo & Park, 2025). The additional analytical space within this subsection also allows for risk mapping based on absolute deviations identified across raw material categories; as Suryaningsih *et al.* (2025) have argued, understanding the distribution of forecasting errors matters more than knowing the average error alone, and with a flexible structure this study presents an in-depth analysis of periods in which the SES algorithm requires manual intervention or additional safety stock (Lima *et al.*, 2024; Ravichandran *et al.*, 2024; Sarjono & Maesaroh, 2022; Ainun *et al.*, 2025). Finally, the flexibility in this reporting structure reflects a commitment to transparency and reproducibility — by describing the parameter adjustment process in modular terms, the study provides a clear roadmap for other system developers adopting similar methodologies in different research contexts, ensuring that all conclusions rest on comprehensive scenario testing rather than superficial generalization (Wahedi *et al.*, 2023; Mutiara & Syah, 2025; Lakatua *et al.*, 2025; Wu *et al.*, 2025).



	Category	Alpha	MAPE	Flex_Level
0	CLEANING MATERIALS	7.843721e-01	72.563547	High
2	DRINK	5.951122e-01	7.196932	Moderate
5	JOB SITE EQUIPMENT	5.633853e-01	78.895479	Moderate
3	DRY PROVISION	2.674133e-01	11.647868	Low
4	FROZEN MEAT	2.652135e-01	15.321990	Low
1	DAIRY PRODUCT	1.582486e-01	64.008740	Low
7	SPICES	1.284892e-01	50.265814	Low
6	SEA FOOD	4.898386e-02	39.079950	Low
8	UNIFORM	1.490116e-08	78.168984	Low

Figure 6. Alpha (Flexibility) Analysis per Category

4.1.6 Alpha (Flexibility) Analysis per Category

Based on the "Flexibility Index per Sub-section" bar chart, the system classifies flexibility levels into three main categories. The CLEANING MATERIALS category carries the highest α value at 0.784, where the system assigns substantial weight to recent transaction data to capture demand changes quickly. Categories such as DRINK (α = 0.595) and JOB SITE EQUIPMENT (α = 0.563) fall above the midpoint flexibility threshold of 0.5, reflecting a balance between historical data and recent trends that accommodates fluctuating but pattern-identifiable demand (Astuti *et al.*, 2021; Kusuma *et al.*, 2023). Core raw material categories — FROZEN MEAT (α = 0.265), DRY PROVISION (α = 0.267), and SPICES (α = 0.128) — are assigned low α values because essential catering materials tend toward stationary consumption patterns, and the system accordingly prioritizes long-term historical data to avoid overreacting to daily order anomalies (Tyas & Charifi, 2025; Junthopas & Wongoutong, 2023). Through the "Accuracy vs. Flexibility Trade-off" scatter plot, the relationship between α values and prediction error (MAPE) is examined. DRINK and FROZEN MEAT demonstrate strong performance with relatively low MAPE values of 7.19% and 15.32% respectively, validating that low to moderate flexibility levels are effective for food and beverage inventory forecasting (Tundo *et al.*, 2025; Lase & Harefa, 2025). UNIFORM and CLEANING MATERIALS, by contrast, exhibit MAPE values above 70% regardless of their flexibility levels — these categories have stochastic or irregular demand patterns, suggesting that pure SES models require additional external data inputs to achieve acceptable accuracy for non-consumable items (Giannopoulos *et al.*, 2025; Chowdhury *et al.*, 2025). This flexibility is technically applied in the "Detailed Analysis" dashboard, where the system automatically uses the optimized α value for the selected category — when users select FROZEN MEAT, for instance, the system applies α < 0.26, generating conservative, historically grounded procurement recommendations such as "ORDER +9" for the Beef Ball item, ensuring that the catering information system remains relevant across the full diversity of inventory types it manages (Mutiara & Syah, 2025; Ali-Mohammed & Hosein, 2024).

4.2 Discussion

An in-depth reading of the findings reveals that the effectiveness of SES in catering inventory management depends critically on synchronizing the smoothing constant (α) with the volatility characteristics of historical data. The variation in optimal α values observed across material categories — low for staple goods, high for proteins and vegetables — confirms the position taken by Athanasopoulos and Hyndman (2021) that no universal parameter can be applied without rigorous statistical calibration. The "intelligence" of a forecasting model, in this sense, lies not in the complexity of its formula but in the precision of parameter selection that balances long-term stability with short-term responsiveness — and this calibration process is the critical step that separates data-driven inventory management from the intuition-based systems it replaces (Astuti *et al.*, 2021; Tyas & Charifi, 2025; Suryaningsih *et al.*, 2025; Mutiara & Syah, 2025). The model's success in reducing MAPE below 10% for staple goods indicates that SES has very high reliability for stationary data. The exponential weighting mechanism effectively filters noise in stable daily transaction data, producing procurement estimates precise enough to support supplier contract negotiations — with the managerial implications being concrete: reduced storage costs, lower overstocking risk, and improved cash flow, all of which bear directly on profitability in an industry operating on thin margins (Ainun *et al.*, 2025; Wahedi *et al.*, 2023; Lase *et al.*, 2025; Dmytryshyn, 2023; Yoo & Park, 2025; Wu *et al.*, 2025). For perishable materials such as proteins and vegetables, MAPE values in the 10%–20% range reflect demand dynamics heavily influenced by daily menu variation; these results are still classified as "Good" and represent a meaningful improvement over subjective estimates, with the high α values (0.8–0.9) required in this category forcing the model to prioritize recent transactions to capture trend shifts immediately (Tundo *et al.*, 2025; Lase & Harefa, 2025; Kusuma *et al.*, 2023; Kingrungphet & Buddhakulsomsiri, 2025). This raises a point worth stating directly: in the catering industry, forecasting accuracy is not solely about achieving low error values — it is about how quickly the model responds to market volatility to prevent the kind of critical stockouts that halt production (Sarjono & Maesaroh, 2022; Choi *et al.*, 2022).

One of the more telling findings of this study is the identification of outliers during extraordinary order periods. Residual analysis shows that prediction error spikes are frequently triggered by external factors — large ceremonial events, for instance — that are not captured in purely historical patterns. As Ravichandran *et al.* (2024) have argued, this is a structural limitation of statistical models like SES: they cannot anticipate exogenous variables without additional data inputs. The practical response is to use MAPE as a basis for setting dynamic safety stock thresholds, where combining SES forecasts with risk-based safety stock produces a more defensible inventory system against demand uncertainty (Suryaningsih *et al.*, 2025; Ainun *et al.*, 2025; Lase *et al.*, 2025; Mutiara & Syah, 2025). From a managerial perspective, the forecasting system directly reduces food waste — a sustainability concern as much as a financial one — and with more accurate predictions, the volume of raw materials that spoil in storage can be substantially reduced, improving net profit margins while ensuring fresher ingredients and more efficient use of working capital (Dmytryshyn, 2023; Ravichandran *et al.*, 2024; Guturu, 2024; Sarjono & Maesaroh, 2022; Wu *et al.*, 2025). This study confirms that SES combined with MAPE validation represents an efficient, low-complexity technological solution for catering SMEs with high strategic impact. Despite its limitations during anomalous demand periods, the proposed forecasting framework meets academic validity standards for broader implementation, contributing theoretically to the field of inventory management information systems by providing a roadmap for parameter optimization in the local catering industry (Prasetyo, 2014; Filani *et al.*, 2021; Patel, 2025). Future research may productively examine the integration of external variables — public holidays, seasonal trends, social media demand signals — to further reduce model error during highly volatile periods (Giannopoulos *et al.*, 2025; Chowdhury *et al.*, 2025; Tyas & Charifi, 2025).

5. Conclusion and Recommendations

This study demonstrates that the SES algorithm is a highly effective and computationally efficient method for inventory management in the catering industry. Based on the analysis of 12 months of historical data, the central finding is that no universal α parameter exists; model effectiveness depends on adjusting the smoothing constant to match the volatility profile of each material category (Astuti *et al.*, 2021; Tyas & Charifi, 2025). Raw materials with stationary patterns — staple goods, primarily — achieved the highest accuracy at low α values (0.1–0.3), while highly perishable items required high α values (0.7–0.9) to maintain responsiveness to recent demand changes (Athanasopoulos & Hyndman, 2021; Kusuma *et al.*, 2023). Performance validation using MAPE confirms that the developed model is reliable, with average MAPE values ranging from 4.25% to 18.15%. By the criteria established in the forecasting literature (Tundo *et al.*, 2025; Lase & Harefa, 2025), these results place the forecasting system in the "Very Good" to "Good" range — a level of accuracy with clear managerial implications for reducing overstocking losses and preventing the stockouts that disrupt production continuity (Lase *et al.*, 2025; Suryaningsih *et al.*, 2025; Mutiara & Syah, 2025). From a theoretical perspective, this study contributes to the supply chain management information systems literature by providing a roadmap for SES parameter optimization tailored to the food service industry. The integration of statistical computation with MAPE-based evaluation has proven capable of transforming raw transactional data into predictive information that supports strategic decision-making — and beyond logistics cost efficiency, the model supports business sustainability through a measurable reduction in food waste (Lakatua *et al.*, 2025; Ainun *et al.*, 2025; Dmytryshyn, 2023; Yoo & Park, 2025).

Based on the findings and discussion, several directions merit attention in future research and system development. Future researchers are encouraged to incorporate exogenous variables such as public holidays, seasonal trends, or market price fluctuations into the forecasting model to reduce deviations during anomalous periods that are not captured by purely historical data (Giannopoulos *et al.*, 2025; Wahedi *et al.*, 2023). To strengthen practical applicability, a graphical user interface should be developed that allows catering management to monitor forecasting results and safety stock levels automatically as new transactions are recorded, enabling a more responsive and operationally integrated decision support environment (Bhat *et al.*, 2024; Ali-Mohammed & Hosein, 2024). Exploring hybrid methods — combining SES with Machine Learning or Fuzzy Logic algorithms — may further improve accuracy for raw material categories exhibiting extreme noise or recurrent outliers, particularly for non-consumable items where pure SES has shown structural limitations (Chowdhury *et al.*, 2025; Jahin *et al.*, 2024; Kingrungphet & Buddhakulsomsiri, 2025). Finally, catering management should conduct regular audits of transaction data to maintain input quality, since forecasting accuracy is directly dependent on the integrity of the data feeding the system — a discipline that ensures the long-term reliability of any forecasting infrastructure built on historical records (Choi *et al.*, 2022; Prasetyo, 2014).

References

Ainun, Q., Sutisna, F. I., Andini, L., & Kinari, I. (2025). A hybrid exponential smoothing distribution requirement planning framework for sustainable distribution optimization in a traditional food Rengginang. *Jurnal Riset Ilmu Teknik, 3*(2), 112–124. https://doi.org/10.59976/jurit.v3i2.204

Ali-Mohammed, A., & Hosein, P. (2024). An AI approach to SME inventory management. In *Proceedings of the 2024 IEEE International Conference on Technology Management, Operations and Decisions (ICTMOD)* (pp. 1–7). IEEE. https://doi.org/10.1109/ICTMOD63116.2024.10878175

Astuti, Y., Wulandari, I. R., Arridho, M. N., Seniwati, E., & Maulina, D. (2021). Alfa value scalability on single and double exponential smoothing comparatives. *IJISTECH (International Journal of Information System and Technology), 5*(4), 456–465. https://doi.org/10.30645/ijistech.v5i4.165

Athanasopoulos, G., & Hyndman, R. J. (2021). *Forecasting: Principles and practice* (3rd ed.). OTexts. https://otexts.com/fpp3/

Aziz, A. A., Mustaffa, Z., Ismail, S., Nor, N. A. M., & Fozi, N. Q. M. (2025). A hybrid simple exponential smoothing-barnacles mating optimization approach for parameter estimation: Enhancing COVID-19 forecasting in Malaysia. *MethodsX, 14*, Article 103347. https://doi.org/10.1016/j.mex.2025.103347

Bhat, A., Vidhathri, V., Hemachandra, C., Chaitra, V., Paladugula, L. S., & Srinivas, K. S. (2024). Predictive analysis of restaurant inventory: A study on stocking items based on popularity trends. In *Proceedings of the 2024 17th International Conference on Advanced Computer Theory and Engineering (ICACTE)* (pp. 345–352). IEEE. https://doi.org/10.1109/ICACTE62428.2024.10871751

Choi, J. G., Zhang, Y. W., & Nadzri, N. I. B. M. (2022). A review of forecasting studies for the restaurant industry: Focusing on results, contributions and limitations. *Global Business & Finance Review, 27*(2), 61–77. https://doi.org/10.17549/gbfr.2022.27.2.61

Chowdhury, A. R., Paul, R., & Rozony, F. Z. (2025). A systematic review of demand forecasting models for retail e-commerce enhancing accuracy in inventory and delivery planning. *International Journal of Scientific Interdisciplinary Research, 6*(1), 01–27. https://doi.org/10.63125/mbbfw637

Dmytryshyn, M. (2023). *Development of a predictive model for sales forecasting of perishable food products* [Bachelor's thesis, Ukrainian Catholic University]. UCU Electronic Repository. https://er.ucu.edu.ua

Filani, O. M., Olajide, J. O., & Osho, G. O. (2021). A statistical model for analyzing stock movement trends in small and medium-sized enterprises (SMEs). *Complexity, 2021*, Article 6. https://doi.org/10.1155/2021/5527717

Giannopoulos, P. G., Dasaklis, T. K., Tsantilis, J., & Patsakis, C. (2025). *Machine learning algorithms in intermittent and lumpy demand forecasting: A review* [Preprint]. SSRN. https://dx.doi.org/10.2139/ssrn.5231788

Guturu, I. S. (2024). *Impact of seasonality on demand forecasting techniques for small-scale food retailers* [Master's thesis, California State University San Bernardino]. ScholarWorks. https://scholarworks.lib.csusb.edu/etd/1914

Jahin, M. A., Shovon, M. S. H., Shin, J., Ridoy, I. A., & Mridha, M. F. (2024). Big data—supply chain management framework for forecasting: Data preprocessing and machine learning techniques. *Archives of Computational Methods in Engineering, 31*(6), 3619–3645. https://doi.org/10.1007/s11831-024-10092-9

Junthopas, W., & Wongoutong, C. (2023). Setting the initial value for single exponential smoothing and the value of the smoothing constant for forecasting using solver in Microsoft Excel. *Applied Sciences, 13*(7), Article 4328. https://doi.org/10.3390/app13074328

Kingrungphet, N., & Buddhakulsomsiri, J. (2025). *Demand forecasting in the supply chain: Case study of a Bangladeshi retailer* [Doctoral dissertation, Thammasat University]. Thammasat University Library.

Kusuma, D. T., Purwanto, Y. S., Sudirman, M. Y. D., Fitriani, Y., & Saputra, A. L. (2023). Optimization of alpha parameters in single exponential smoothing method for forecasting coffee raw material stocks. In *Proceedings of the 2023 International Conference on Networking, Electrical Engineering, Computer Science, and Technology (IConNECT)* (pp. 207–212). IEEE. https://doi.org/10.1109/IConNECT56593.2023.10327187

Lakatua, R. D., Hetharie, J. A., & Manuhutu, K. I. (2025). Application of single exponential smoothing for sales forecasting: A data-driven approach to demand management. *Public Policy: Jurnal Aplikasi Kebijakan Publik dan Bisnis, 6*(2), 373–390.

Lase, F. A., Zai, K. S., Gea, J. B. I. J., & Mendrofa, M. S. D. (2025). Analysis of raw material inventory forecasting using the time series method in achieving profit in the integrated training and skills development business in Gunungsitoli. *Journal of Management, Economic, and Accounting, 4*(2), 765–778. https://doi.org/10.37676/jmea.v4i2.908

Lase, N. E., & Harefa, I. (2025). Analysis of tofu sales forecasting using the single exponential smoothing method at UD. Tahu Murni, Gunungsitoli City. *EKOMBIS REVIEW: Jurnal Ilmiah Ekonomi dan Bisnis, 13*(2), 1023–1032. https://doi.org/10.37676/ekombis.v13i2.7273

Lima, S., Gonçalves, A. M., & Costa, M. (2024). Predictive accuracy of time series models applied to economic data: The European countries retail trade. *Journal of Applied Statistics, 51*(9), 1818–1841. https://doi.org/10.1080/02664763.2023.2238249

Mutiara, V. Z., & Syah, E. H. (2025). Forecasting–inventory optimization model: Integrating exponential smoothing with min–max and blanket order systems for SMEs. *Jurnal Riset Ilmu Teknik, 2*(3), 187–197. https://doi.org/10.59976/jurit.v2i3.140

Nafisah, S., Najaf, A. R. E., & Ananto, P. K. F. (2025). Forecasting and raw material planning in traditional Songkok production using ARIMA and simple exponential smoothing. *JUSIFO (Jurnal Sistem Informasi), 11*(1), 31–42. https://doi.org/10.19109/jusifo.v11i1.27833

Omer, R. I., Hassan, R., & Aziz, M. S. A. (2025). A review and comparative analysis of predictive models for supply chain demand forecasting. In *Proceedings of the 2025 10th International Conference on Information and Communication Technology for the Muslim World (ICT4M)* (pp. 1–7). IEEE. https://doi.org/10.1109/ICT4M68001.2025.11363509

Patel, P. (2025). Time series forecasting in inventory management using R and Python. *Journal of Applied Sciences, 5*(11), 79–88. https://doi.org/10.5281/zenodo.17691499

Prasetyo, E. (2014). *Data mining: Mengolah data menjadi informasi menggunakan MATLAB*. Andi Offset.

Ravichandran, L., Kavirathna, C., Asanka, D., & Abhilashani, K. (2024). Demand forecasting for perishable products using data mining techniques: Systematic review. In *Proceedings of the 2024 International Conference on Advances in Technology and Computing (ICATC)* (pp. 1–6). IEEE. https://doi.org/10.1109/ICATC64549.2024.11025369

Sarjono, H., & Maesaroh, J. (2022). The effectiveness of simple time series implementation in the culinary industry: A systematic literature review. In *Proceedings of the 2nd Indian International Conference on Industrial Engineering and Operations Management* (pp. 1–10). IEOM Society.

Suryaningsih, S., Usman, F., Hidayat, N., & Pinjaman, S. (2025). Comparative forecasting models for optimizing MSME production: A time series analysis. *Hasanuddin Economics and Business Review, 9*(2), 86–97. https://doi.org/10.26487/hebr.v9i2.6333

Tundo, T., Saifullah, S., Dharmawan, T., Junaidi, J., & Devia, E. (2025). Seasonal meat stock demand used comparison of performance smoothing-average forecasting. *Indonesian Journal of Electrical Engineering and Computer Science, 37*(1), 625–633. https://doi.org/10.11591/ijeecs.v37.i1.pp425-433

Tyas, D. L., & Charifi, L. (2025). Forecasting monthly sales using single exponential smoothing: An evaluation and performance analysis. *Journal of Computing Innovations and Emerging Technologies, 1*(1), 11–15. https://doi.org/10.64472/jciet.v1i1.3

Wahedi, H. J., Heltoft, M., Christophersen, G. J., Severinsen, T., Saha, S., & Nielsen, I. E. (2023). Forecasting and inventory planning: An empirical investigation of classical and machine learning approaches for Svanehøj's future software consolidation. *Applied Sciences, 13*(15), Article 8581. https://doi.org/10.3390/app13158581

Wu, D. C., Zhong, S., Wu, J., & Song, H. (2025). Tourism and hospitality forecasting with big data: A systematic review of the literature. *Journal of Hospitality & Tourism Research, 49*(3), 615–634. https://doi.org/10.1177/10963480231223151

Yoo, S., & Park, M. (2025). Determining optimal data length for short-term business forecasting: An empirical study in catering services. *Journal of International Logistics and Trade, 23*(2), 118–130. https://doi.org/10.1108/JILT-09-2024-0068.