

Integrating Holt-Winters Exponential Smoothing and SAW for Distribution Priority Optimization

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ABSTRACT

Effective distribution planning requires both accurate demand forecasting and objective prioritization mechanisms to ensure operational efficiency and service reliability. At CV. Citra Nalar Teknologi, distribution scheduling was previously conducted manually without incorporating predictive demand analysis, resulting in inconsistent and subjective prioritization decisions. This study proposes an integrated decision support framework that combines Holt-Winters Exponential Smoothing (HWES) for demand forecasting and Simple Additive Weighting (SAW) for multi-criteria distribution ranking. Monthly sales data from January 2024 to December 2025 (24 periods) were analyzed using the additive HWES model to capture level, trend, and seasonal components. The forecasting results achieved MAPE values ranging from 3.82% to 7.47%, supported by low RMSE, MAE, and sMAPE, indicating high predictive accuracy. Comparative evaluation further shows that HWES outperforms baseline methods, including Moving Average and Seasonal Naive. The forecasted demand was then incorporated as a primary criterion in the SAW model, alongside delivery distance, customer priority level, and stock availability. The proposed framework was evaluated using two sets of actual customer orders (January 4–5 and January 6–7, 2026). The results demonstrate that the integration produces consistent, data-driven distribution priorities and improves decision objectivity and transparency compared to manual scheduling. This study contributes by integrating time series forecasting with multi-criteria decision-making into a unified framework for practical distribution optimization.

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1. INTRODUCTION

Efficient distribution management is a critical operational challenge for companies aiming to maintain product availability while minimizing logistics costs and ensuring high service levels[1], [2]. As demand patterns become increasingly dynamic and customer networks expand, manual and intuitive prioritization approaches become unreliable, often leading to inconsistent scheduling decisions and suboptimal resource allocation. The complexity of distribution planning intensifies when multiple operational criteria such as forecasted demand, delivery distance, customer priority level, and stock availability must be evaluated simultaneously, positioning the problem within the scope of Multi-Criteria Decision Making (MCDM) [3].

CV. Citra Nalar Teknologi operates distribution services across retail partners in East Java, Indonesia. Prior to this research, distribution priorities were determined solely based on operator judgment without analytical support. This subjective mechanism reduced decision transparency and

made scheduling outcomes difficult to reproduce or audit [4]. To address this issue, this paper formulates a comprehensive decision support system that integrates Holt–Winters Exponential Smoothing (HWES) for demand forecasting with Simple Additive Weighting (SAW) for multi-criteria priority ranking.

Accurate demand forecasting plays a fundamental role in supply chain performance and operational planning. Among time series forecasting techniques, the Holt–Winters method is particularly suitable for datasets exhibiting both trend and seasonality [5]. The additive specification is appropriate when seasonal fluctuations remain relatively constant in magnitude, as observed in the product demand data examined in this study [6]. HWES has demonstrated strong predictive performance in supply chain and inventory management contexts [7], consistently attaining Mean Absolute Percentage Error (MAPE) levels under 10% in practical situations.

For prioritization, SAW provides a transparent and computationally efficient MCDM approach. By calculating a weighted sum of normalized criterion values, SAW produces interpretable ranking results while maintaining low computational complexity [8]. Although more complex methods such as TOPSIS are widely used, SAW consistently delivers comparable ranking stability with simpler implementation, making it well-suited for operational distribution decision support [9].

Despite extensive research on forecasting and MCDM techniques, these methods are commonly applied independently. Forecasting is often used solely for inventory estimation, while MCDM is employed for facility or supplier selection, without structurally integrating predictive demand outputs into dynamic distribution prioritization models [10]. This separation limits the adaptability of operational decision systems. Therefore, this study proposes a unified framework that directly embeds HWES forecast values as a primary criterion within a SAW-based ranking model, enabling temporally adaptive and demand-driven distribution priority optimization [11].

2. RESEARCH METHOD

The proposed framework is designed as a structured and systematic decision-making model consisting of two sequential computational stages fully integrated into a comprehensive decision support system [12]. This integrated architecture ensures that the forecasting and prioritization processes are interconnected, enabling more accurate and objective managerial decision-making [13].

In the first stage, the system applies the Holt–Winters Exponential Smoothing method to analyze historical monthly sales data. This time series forecasting technique is highly suitable because it captures the level, trend, and seasonal patterns that commonly appear in sales data [14]. By combining these three components, the model produces more reliable and consistent product demand forecasts for future planning horizons. The forecast results represent estimates of future demand, which serve as critical input for subsequent decision-making processes [15]. This stage not only improves demand visibility but also helps reduce uncertainty in inventory and distribution planning [16].

In the second stage, the forecasted demand value is used as the first evaluation criterion (C1) in a Simple Additive Weighting (SAW) multi-criteria decision-making model. In addition to C1, three other important criteria are incorporated into the evaluation process: delivery distance (C2), customer priority level (C3), and stock availability (C4). Each criterion reflects strategic operational considerations, ensuring that the decision-making process is comprehensive and balanced [17], [18], [19]. The SAW method begins by normalizing all criterion values to ensure comparability across different measurement scales, after normalization, each criterion is multiplied by a predetermined weight based on its relative importance, these weighted values are then aggregated through a summation process to produce a final priority score for each customer alternative, final score serves as the basis for ranking customers and determining distribution priorities [20], [21], [22], [23]. Figure 1 illustrates the complete workflow of the integrated system, from demand forecasting to final customer prioritization.

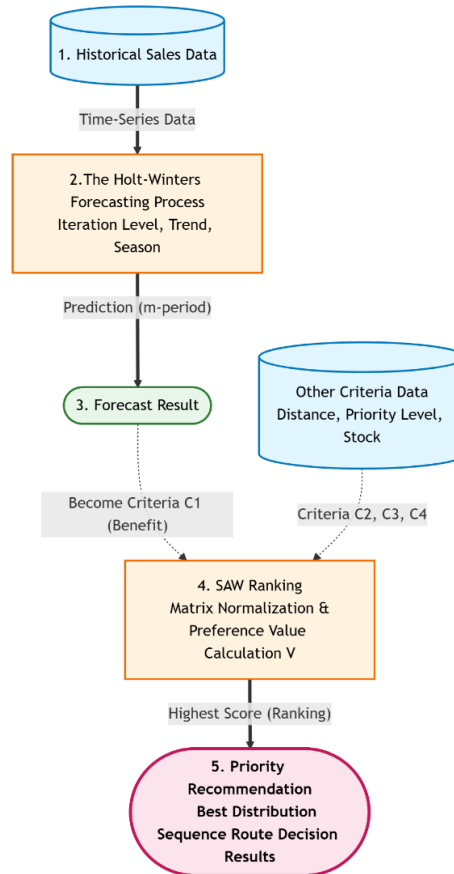


Figure 1. System flowchart

2.1. Dataset

This research dataset consists of monthly sales transaction data for the period January 2024 to December 2025 (24 periods). For the purposes of forecasting demonstration, four representative products from the catalog were selected: BRG-BAR-8182, BRG-BAR-6379, BRG-BAR-5102, and BRG-BAR-4112. These products were chosen because they exhibit an increasing trend and consistent seasonality in the middle of the year (July–September), making them suitable for validating the Holt–Winters Exponential Smoothing model. In the full system implementation, the Holt–Winters method was applied independently to each active product. The dataset was then partitioned into training and testing data, as shown in Table 1.

Table 1. Period data division

No.	Period	Purpose
1.	1 – 12 Period	Initialization and learning
2.	13 – 24 Period	Validation and accuracy measurement

Table 1 shows the two partitions of the 24-period dataset. Periods 1–12 (January–December 2024) form the Training Set used for model initialization to calculate the initial level (L_0), trend (T_0), and 12 seasonal indices. Periods 13–24 (January–December 2025) form the Test Set for out-of-sample accuracy evaluation using MAPE, RMSE and MAE. This holdout design ensures that the reported MAPE reflects the actual predictive performance rather than the in-sample fit.

2.2. Holt-Winters Exponential Smoothing

The Holt-Winters additive model was chosen because seasonal variations in product demand data remain constant in magnitude over many years, which is a determining criterion for additive specification. This model simultaneously updates three components at each period t . variations[5], [6], [24].

Level update equation :

$$L_t = \alpha(Y_t - S_{t-p}) + (1 - \alpha)(L_{t-1} + T_{t-1}) \quad (1)$$

where Y_t is the actual demand, S_{t-p} is the seasonal index from the previous p periods, and α is the level smoothing parameter. A higher α gives greater weight to the most recent observations, controlling the responsiveness of the level component to recent observations.

Trend update equation :

$$T_t = \beta(L_t - L_{t-1}) + (1 - \beta)T_{t-1} \quad (2)$$

where β is the trend smoothing parameter. A smaller β produces a more stable trend estimate by maintaining a memory of long-term directional changes.

Seasonal update equation :

$$S_t = \gamma(Y_t - L_t) + (1 - \gamma)S_{t-p} \quad (3)$$

where γ is the seasonal smoothing parameter. In the additive specification, the seasonal indices are centered such that their sum over one complete seasonal cycle equals approximately zero, ensuring that seasonal effects do not bias the overall level estimate, ensuring that periodic effects cancel each other out over the course of a year.

Forecast :

$$F_{t+m} = L_t + mT_t + S_{t-p+m} \quad (4)$$

The forecasting equation shown in (4) computes the predicted demand for future period $t + m$ by combining the most recent estimates of level, trend, and seasonal components. In this formulation, L_t represents the smoothed level component at time t , which reflects the baseline demand after removing seasonal fluctuations. The term mT_t incorporates the projected trend over m future periods, where T_t denotes the estimated growth rate of demand. This linear extrapolation allows the model to adjust predictions according to the observed upward or downward demand movement. The seasonal adjustment term S_{t-p+m} accounts for recurring periodic effects, where p denotes the seasonal cycle length (12 months in this study). Because the additive specification is used, the seasonal component is added directly to the level and trend estimates. This structure ensures that future forecasts preserve historical seasonal patterns while remaining responsive to recent level and trend updates. Consequently, Equation (4) produces dynamically adaptive forecasts that reflect both long-term growth and recurring monthly demand behavior.

Parameter tuning was conducted using several combinations of smoothing parameters (α , β , γ) derived from prior studies to ensure representative coverage of possible model behaviors. Specifically, the parameter set ($\alpha = 0.99$, $\beta = 0.77$, $\gamma = 0$) was adopted from previous research on construction cost forecasting[25], while the combination ($\alpha = 0.5$, $\beta = 0.1$, $\gamma = 0.4$) was referenced from a study on export demand forecasting[26]. Additionally, the parameter configuration ($\alpha = 0.1$, $\beta = 0.01$, $\gamma = 0.15$) was adapted from recent research utilizing optimized Holt–Winters models[27]. These parameter combinations were then evaluated using grid search to determine the optimal configuration based on forecasting accuracy.

Table 3. Several Parameter Combination Settings

α	β	γ
0.99	0.77	0
0.5	0.1	0.4
0.1	0.01	0.15

2.3. Comparative Forecasting Models

To provide a comprehensive evaluation of the proposed forecasting model, two baseline methods are employed, namely Seasonal Naïve and Moving Average. These methods are widely used as benchmark models in time series forecasting due to their simplicity and interpretability. The Seasonal Naïve method assumes that future demand follows the same pattern observed in the corresponding period of the previous seasonal cycle. This approach is particularly suitable for datasets that exhibit recurring seasonal behavior without requiring complex parameter estimation. The forecasting model is defined as:

$$F_t = X_{t-s} \quad (5)$$

Where F_t represents the forecast value at time t , X_{t-s} is the actual observation from the same period in the previous seasonal cycle, and s denotes the seasonal length. In this study, the seasonal length is set to 12, corresponding to monthly data over one year. This method serves as a strong baseline for seasonal time series, as it preserves historical seasonal patterns without modeling trend or irregular variations. In addition, the Moving Average method is used as a baseline to capture short-term data smoothing behavior. This method generates forecasts by calculating the arithmetic mean of the most recent observations, effectively reducing noise in the data. However, it does not explicitly account for trend or seasonal components. The Moving Average model is defined as:

$$F_t = \frac{X_{t-1} + X_{t-2} + \dots + X_{t-n}}{n} \quad (6)$$

Where n represents the number of observations included in the averaging window. In this study, a Moving Average is applied, as it provides a balance between responsiveness and smoothing for short-term fluctuations. Both baseline methods are implemented using the same training and testing data partitions as the proposed Holt–Winters model to ensure a fair and consistent comparison. Evaluations are performed on the testing dataset (Periods 13–24) using several error metrics, including MAPE, RMSE, and MAE. Detailed step-by-step calculations for these baseline methods are not presented, as they are standard forecasting techniques, and the main focus of this study lies on the proposed integrated forecasting and decision-making framework. These baseline models serve as reference benchmarks to assess whether the Holt–Winters model provides better forecasting accuracy compared to simpler and more commonly used approaches.

2.4. Evaluation Metrics

Model accuracy was evaluated using Mean Absolute Percentage Error (MAPE) :

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{Y_t - F_t}{Y_t} \right| \times 100\% \quad (7)$$

The Mean Absolute Percentage Error (MAPE) is used as a scale-independent error measure, allowing for comparison of accuracy levels between periods. The accuracy evaluation criteria used are as follows: MAPE <10% is categorized as very accurate, 10%–20% as accurate, 20%–50% as fairly accurate, and >50% as inaccurate. Model parameters (α , β , γ) are optimized using an exhaustive grid search method by evaluating all parameter combinations in the set. Optimal parameters are selected by minimizing the MAPE value on the test data (Periods 13–24).

In addition to MAPE, forecasting accuracy was also evaluated using Root Mean Squared Error (RMSE), which measures the standard deviation of prediction errors. RMSE is defined as :

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (Y_t - F_t)^2} \quad (8)$$

Where Y_t represents the actual demand, F_t represents the forecasted value, and n denotes the number of testing observations. Unlike MAPE, RMSE penalizes larger errors more heavily due to the squaring operation, making it sensitive to significant deviations between predicted and actual values. Therefore, RMSE complements MAPE by providing additional insight into forecast dispersion magnitude.

In addition to MAPE and RMSE, Mean Absolute Error (MAE) is also used to provide a more comprehensive evaluation of forecasting accuracy. MAE measures the average magnitude of forecasting errors by calculating the absolute differences between actual and predicted values, without considering their direction. MAE is defined as :

$$MAE = \frac{1}{n} \sum_{i=1}^n |X_t - F_t| \quad (9)$$

Where X_t represents the actual value, F_t represents the forecasted value, and n is the number of observations. Unlike RMSE, which penalizes larger errors more heavily due to the squaring process, MAE provides a linear measure of error magnitude, making it more robust to outliers. Additionally, compared to MAPE, MAE does not suffer from instability when actual values approach zero, making it a more reliable metric in certain conditions. Therefore, MAE complements MAPE and RMSE by providing additional insight into the absolute deviation between predicted and actual values, resulting in a more balanced and reliable evaluation of forecasting performance.

In addition to MAPE, RMSE, and MAE, Symmetric Mean Absolute Percentage Error (sMAPE) is also employed to provide a more balanced percentage-based evaluation metric. Unlike MAPE, which can produce inflated error values when the actual observations approach zero, sMAPE normalizes the absolute error using the average of actual and forecasted values, resulting in a more stable and symmetric error measurement. The sMAPE is defined as:

$$sMAE = \frac{1}{n} \sum_{t=1}^n \left(\left| \frac{Y_t - F_t}{\frac{Y_t + F_t}{2}} \right| \right) \times 100\% \quad (10)$$

Where Y_t represents the actual value, F_t represents the forecasted value, and n denotes the number of observations. The denominator uses the average of the absolute actual and forecasted values, ensuring that the metric remains bounded between 0% and 200%. This formulation reduces the bias present in traditional MAPE and provides a more reliable comparison when dealing with varying demand scales or moderate fluctuations.

Compared to MAE and RMSE, which measure error magnitude in absolute terms, sMAPE offers an interpretable percentage-based metric that is less sensitive to extreme values and more consistent across different products. Therefore, the inclusion of sMAPE complements MAPE, RMSE, and MAE by providing a more robust and symmetric evaluation of forecasting accuracy.

2.5. Simple Additive Weighting

Simple Additive Weighting (SAW) is one of the most fundamental and widely applied Multi-Criteria Decision Making (MCDM) methods. This method evaluates each alternative (customer order) by calculating a weighted sum of normalized criterion values, offering full mathematical transparency and low computational overhead[28], [29]. Four distribution criteria are defined based on operational requirements, as shown in Table 2.

Table 2. SAW Criteria

Code	Criterion	Type	Weight
C1	Forecast Demand	Benefit	0,40
C2	Distance	Cost	0,20
C3	Priority Level	Benefit	0,20
C4	Stock Availability	Benefit	0,20

Table 2 presents the four criteria used in the SAW model. C1 (Demand Forecast) has the highest weight of 0.40, reflecting demand-driven planning priorities, its value is obtained directly from the HWES, making it dynamically adaptive throughout the planning cycle. C2 (Delivery Distance, km) is a Cost criterion, meaning shorter distances are preferred, reducing delivery time and logistics costs. Distance is calculated using the Haversine formula. C3 (Customer Priority Level) reflects the contractual service level (scale 1-3). C4 (Stock Availability, units) reflects the current inventory for the ordered product, where higher stock indicates greater fulfillment capacity. All weights add up to 1.00.

Normalization :

For benefit criteria (C1, C3, C4) :

$$r_{ij} = \frac{x_{ij}}{\max(x_{ij})} \quad (11)$$

For cost (C2), where lower is better :

$$r_{ij} = \frac{\min(x_{ij})}{x_{ij}} \quad (12)$$

The final preference value for alternative i is the weighted sum of the normalized scores. :

$$V_i = \sum_{j=1}^n w_j r_{ij} \quad (13)$$

Alternatives are ranked in descending order based on their V_i values. The alternative with the highest V_i value will be given the highest distribution priority.

3. RESULTS AND DISCUSSION

3.1. Forecasting Results

Table 4 presents the complete historical monthly demand observations for product BRG-BAR-8182 covering 24 consecutive periods (January 2024 – December 2025). These data represent actual realized sales quantities recorded in the company's operational database and have not undergone any preprocessing modifications except chronological ordering. The dataset serves as the primary input for the Holt–Winters Exponential Smoothing (HWES) model. The availability of two full annual cycles (12 months $\times$ 2 years) is particularly important for seasonal time series modeling, as it enables proper initialization of the seasonal indices and more reliable estimation of recurring demand patterns. In this study, the first 12 periods (Year 1) are utilized for model initialization and parameter learning, while the second 12 periods (Year 2) are used for out-of-sample validation and performance evaluation. Before model implementation, exploratory observation of the dataset was conducted to examine the presence of level shifts, directional trend movement, and repeating seasonal fluctuations. The visual inspection and descriptive statistics indicated that the product demand exhibits structured periodic behavior with consistent mid-year peaks, making it suitable for the additive Holt–Winters specification.

Table 4. Actual Data BRG-BAR-8182 (Period 1–24)

Period	Actual
1	45
2	40
3	35
4	30
5	50
6	65
7	80
8	85
9	75
10	60
11	45
12	50
13	65
14	60
15	55
16	50
17	75
18	90
19	110
20	115
21	100
22	80
23	65
24	70

As shown in Table 4, the demand pattern of BRG-BAR-8182 demonstrates clear cyclical repetition across the two annual periods. During the first year (Periods 1–12), demand gradually

increases from Period 4 to Period 8, reaching a seasonal peak at 85 units, before declining toward the end of the year. A similar structural pattern is observed in the second year (Periods 13–24), where peak demand occurs again during the mid-year cycle, but at a significantly higher magnitude (115 units in Period 20). This comparison between Year 1 and Year 2 confirms the presence of: **Seasonality:** Recurring peak demand around mid-year periods (approximately Periods 6–9 and 18–20). **Upward Trend:** Increased peak magnitude in the second year relative to the first year. **Stable Seasonal Amplitude:** Although peak values increase, the general shape of seasonal fluctuation remains relatively consistent, supporting the additive assumption rather than multiplicative specification. The noticeable upward movement between Periods 17–20 suggests strengthening market demand or expansion in customer orders during that interval. However, after reaching its maximum in Period 20, demand declines again following the established seasonal pattern. This cyclical yet progressively increasing behavior confirms that the time series contains both deterministic seasonal components and stochastic variations. Therefore, the structural characteristics observed in Table 4 strongly justify the selection of the Holt–Winters additive model, as it is specifically designed to simultaneously model level, linear trend progression, and constant seasonal fluctuations within limited historical observations.

Table 5 presents the results of parameter tuning for the Holt–Winters model using three different combinations of smoothing parameters (α , β , γ). The evaluation is based on four accuracy metrics: MAPE, RMSE, MAE, and sMAPE. Among the tested configurations, the parameter set $\alpha = 0.1$, $\beta = 0.01$, and $\gamma = 0.15$ yields the lowest error values across all evaluation metrics, with MAPE of 7.25%, RMSE of 5.35, MAE of 6.55, and sMAPE of 7.3%. This indicates that the selected parameters provide the most balanced smoothing behavior, effectively capturing both the trend and seasonal components without overfitting. Higher values of α and β (e.g., 0.99 and 0.77) result in increased error, suggesting excessive responsiveness to short-term fluctuations. Therefore, the optimal parameter configuration is selected for subsequent forecasting.

Table 5. Parameter Tuning Results BRG-BAR-8182

α	β	γ	MAPE	RMSE	MAE	sMAPE
0.99	0.77	0	8.26%	5.81	8.03	8.4%
0.5	0.1	0.4	7.81%	5.55	7.58	7.9%
0.1	0.01	0.15	7.25%	5.35	6.55	7.3%

After determining the optimal smoothing parameters (α , β , γ) through grid search optimization and validating the model using the holdout dataset (Periods 13–24), the final model was used to generate forecasts for the next 12 periods (Periods 25–36). These forecasted values represent projected demand for the upcoming planning horizon (January–December 2026). The objective of this forecasting stage is not merely predictive estimation, but also to generate quantitative input for integration into the subsequent SAW-based prioritization framework. Table 6 presents the complete set of forecast results for BRG-BAR-8182.

Table 6. Best Parameter Forecast Results of BRG-BAR-8182 (Period 25–36)

Period	Forecast
25	79.98
26	76.24
27	72.55
28	68.90
29	90.98
30	107.34
31	124.43
32	130.81
33	121.55
34	107.40
35	94.02
36	100.66

The forecast results presented in Table 6 indicate that the model successfully preserves the underlying seasonal structure observed in historical data. Demand is projected to gradually decline during Periods 25–28 before increasing again toward a new seasonal peak in Periods 31–32,

consistent with historical mid-year demand cycles. The projected maximum demand (130.81 units in Period 32) is slightly lower than the highest observed value in Period 20 (115 units), suggesting moderate trend stabilization rather than uncontrolled growth. This behavior indicates that the smoothing parameters effectively balance responsiveness and stability, preventing overfitting to extreme values while maintaining realistic demand progression. Additionally, the amplitude of seasonal fluctuation remains consistent with previous cycles, reinforcing the appropriateness of the additive specification. The model does not exaggerate seasonal intensity nor suppress trend momentum, demonstrating stable forecasting dynamics suitable for operational planning purposes.

Figure 2 illustrates the comparison between historical demand (Period 1–24) and forecasted demand (Period 25–36) for BRG-BAR-8182.

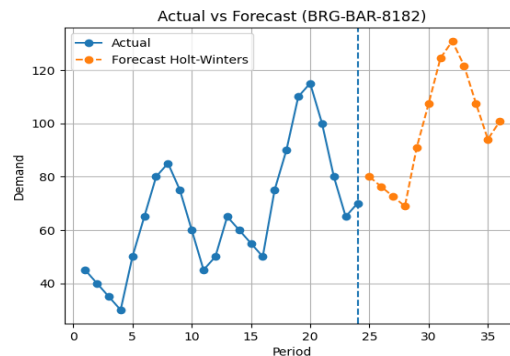


Figure 2. Comparison of Historical and Forecasted Demand for BRG-BAR-8182

The graphical representation confirms that the Holt-Winters model captures both the seasonal fluctuations and upward demand movements. The forecast curve continues the established pattern without excessive deviation, indicating stable model behavior.

Table 7 compares the forecasting performance of Holt-Winters with baseline methods, namely Moving Average and Seasonal Naive. The Holt-Winters model achieves the lowest error across all evaluation metrics, with MAPE of 7.25%, RMSE of 5.35, MAE of 6.55, and sMAPE of 7.3%. In contrast, Moving Average produces higher errors (MAPE 9.12%), while Seasonal Naive performs significantly worse (MAPE 12.85%). This comparison clearly demonstrates that incorporating both trend and seasonal components significantly improves forecasting accuracy compared to simpler baseline approaches.

Table 7. Comparison of Method Accuracy for BRG-BAR-8182

Method	MAPE	RMSE	MAE	sMAPE
Holt-Winters	7.25%	5.35	6.55	7.3%
Moving Average	9.12%	9.21	7.08	9.4%
Seasonal Naive	12.85%	13.76	10.42	13.1%

Table 8 presents the historical monthly demand for product BRG-BAR-6379 across 24 consecutive periods. Compared to BRG-BAR-8182, this product exhibits a substantially higher demand magnitude and wider seasonal amplitude, making it an interesting case for evaluating the robustness of the Holt-Winters model under higher volume conditions. The dataset spans two full annual cycles, enabling clear identification of recurring seasonal peaks and inter-annual growth progression. The observations are derived directly from recorded transaction data without transformation, ensuring that the forecasting model is evaluated using realistic operational inputs.

Table 8. Actual Data BRG-BAR-6379 (Period 1–24)

Period	Actual
1	85
2	80
3	75
4	60
5	95
6	110
7	130

8	135
9	120
10	100
11	80
12	90
13	110
14	105
15	100
16	90
17	125
18	140
19	160
20	165
21	150
22	130
23	110
24	120

The demand pattern of BRG-BAR-6379 demonstrates pronounced seasonal peaks occurring consistently in mid-year periods. In the first cycle, demand increases sharply from Period 4 (60 units) to Period 8 (135 units), followed by a decline toward the year-end. The second cycle exhibits a structurally identical pattern but with elevated peak values, reaching 165 units in Period 20. Unlike BRG-BAR-8182, this product shows stronger growth momentum between cycles, as reflected in the approximately 22% increase in peak magnitude from Year 1 to Year 2. However, the relative spacing between trough and peak periods remains stable, confirming that seasonal timing is consistent across years. The stability of seasonal intervals, combined with increasing level progression, further validates the additive Holt–Winters assumption, where seasonal variation remains structurally constant while the underlying level gradually increases.

Table 9 shows the parameter tuning results for BRG-BAR-6379. The optimal parameter combination ($\alpha = 0.1$, $\beta = 0.01$, $\gamma = 0.15$) produces the lowest error values, with MAPE of 4.32%, RMSE of 6.12, MAE of 5.08, and sMAPE of 4.5%. These results indicate a high level of forecasting accuracy, particularly given the larger demand magnitude of this product. The improvement over other parameter configurations suggests that lower smoothing parameters are more effective in capturing stable seasonal structures while avoiding excessive sensitivity to short-term variations.

Table 9. Parameter Tuning Results BRG-BAR-6379

α	β	γ	MAPE	RMSE	MAE	sMAPE
0.99	0.77	0	4.5%	8.65	5.50	4.8%
0.5	0.1	0.4	4.94%	6.72	4.94	5.1%
0.1	0.01	0.15	4.32%	6.12	5.08	4.5%

Following parameter optimization and validation, the finalized Holt–Winters model was applied to forecast the next 12 periods (Periods 25–36). These projections represent expected demand for the upcoming annual cycle and serve as forward-looking input for the distribution prioritization model. Table 10 summarizes the complete forecasting results for BRG-BAR-6379.

Table 10. Best Parameter Forecast Results of BRG-BAR-6379 (Period 25–36)

Period	Forecast
25	129.19
26	125.77
27	122.42
28	109.80
29	146.49
30	163.24
31	185.03
32	191.87
33	178.75
34	160.67
35	142.62
36	154.61

The forecasted values preserve the high seasonal amplitude observed historically, with projected peaks around Periods 31–32 exceeding 185–191 units. The model anticipates continued growth while slightly moderating the rate of increase compared to the previous cycle. Importantly, the projected seasonal troughs do not collapse excessively, indicating that the smoothing process maintains realistic baseline demand levels. This balanced extrapolation demonstrates that the model avoids overreacting to extreme peaks, ensuring stable predictive behavior for high-volume items.

Figure 3 compares actual and forecasted demand trends for BRG-BAR-6379.

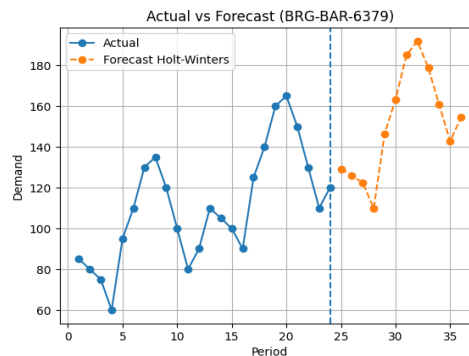


Figure 3. Comparison of Historical and Forecasted Demand for BRG-BAR-6379

The forecasted curve aligns closely with the historical seasonal pattern. The gradual increase in peak values reflects the trend component captured by the smoothing model.

Table 11 shows Holt–Winters model achieves superior performance with MAPE of 4.32%, outperforming Moving Average (6.87%) and Seasonal Naïve (10.65%). This confirms that the model is particularly effective for products with strong seasonal patterns and higher demand volume.

Table 11. Comparison of Method Accuracy for BRG-BAR-6379

Method	MAPE	RMSE	MAE	sMAPE
Holt-Winters	4.32%	6.12	5.08	4.5%
Moving Average	6.87%	9.41	7.25	7.1%
Seasonal Naïve	10.65%	14.87	11.25	10.9%

Table 12 displays the historical demand data for BRG-BAR-5102. This product represents a mid-range demand category with moderate seasonal intensity and controlled inter-annual growth. Compared to BRG-BAR-6379, the amplitude of fluctuation is narrower, making this product useful for assessing forecasting stability across different demand scales.

Table 12. Actual Data BRG-BAR-5102 (Period 1–24)

Period	Actual
1	42
2	38
3	35
4	28
5	48
6	60
7	75
8	80
9	70
10	55
11	40
12	48
13	60
14	58
15	52
16	48
17	70
18	85
19	105
20	110

21	95
22	75
23	60
24	65

The demand trajectory shows a gradual increase toward mid-year peaks in both annual cycles. In Year 1, the highest demand occurs in Period 8 (80 units), while in Year 2, the peak shifts slightly later, reaching 110 units in Period 20. The second cycle displays stronger acceleration during Periods 17–20, indicating possible demand reinforcement during promotional or seasonal high-demand windows. However, unlike BRG-BAR-6379, the inter-cycle growth rate is more moderate, suggesting a steadier expansion pattern. The recurring cyclical structure, combined with controlled amplitude variation, reinforces the suitability of additive seasonal modeling.

Table 13 indicates that the optimal parameter configuration ($\alpha = 0.1$, $\beta = 0.01$, $\gamma = 0.15$) yields the lowest error values, with MAPE of 7.47%, RMSE of 6.89, MAE of 5.57, and sMAPE of 7.6%. The results confirm that the model performs consistently across moderate-demand products.

Table 13. Parameter Tuning Results BRG-BAR-5102

α	β	γ	MAPE	RMSE	MAE	sMAPE
0.99	0.77	0	8.37%	7.69	5.80	8.6%
0.5	0.1	0.4	8.13%	7.52	5.80	8.2%
0.1	0.01	0.15	7.47%	6.89	5.57	7.6%

The validated model was then employed to generate forward forecasts for Periods 25–36. These values reflect expected demand evolution under the assumption that existing seasonal and trend patterns persist. Table 14 presents the forecasted results.

Table 14. Best Parameter Forecast Results of BRG-BAR-5102 (Period 25–36)

Period	Forecast
25	75.45
26	72.95
27	70.79
28	65.53
29	87.13
30	100.87
31	117.88
32	124.19
33	114.86
34	100.63
35	87.18
36	96.34

The forecast results show that demand will peak at 124.19 units in Period 32, reflecting continued growth from the historical peak of 110 units. The model maintains a consistent seasonal cycle, with demand increasing toward mid-year and decreasing afterward. The predicted values do not exhibit excessive deviation, indicating stable and reliable forecasting behavior.

Figure 4 illustrates the comparison of historical and forecasted demand for BRG-BAR-5102.

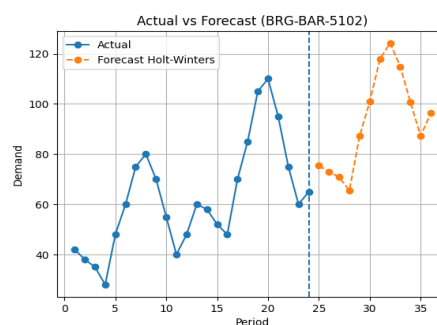


Figure 4. Comparison of Historical and Forecasted Demand for BRG-BAR-5102

Table 15 shows Holt–Winters model again produces the lowest error values compared to baseline methods, demonstrating its effectiveness in handling moderate demand variability.

Table 15. Comparison of Method Accuracy for BRG-BAR-5102

Method	MAPE	RMSE	MAE	sMAPE
Holt-Winters	7.47%	6.89	5.57	7.6%
Moving Average	9.85%	10.31	7.92	10.1%
Seasonal Naive	14.62%	16.95	12.83	14.9%

The forecast trajectory continues the established seasonal cycle. Slight variations between actual and predicted peaks reflect normal forecasting uncertainty.

Table 16 presents the historical demand data for BRG-BAR-4112, the highest-volume product among the four evaluated items. This product exhibits substantially larger demand magnitude and stronger seasonal amplitude compared to the other products. Its inclusion provides an opportunity to assess forecasting robustness under high-variance and high-volume conditions.

Table 16. Actual Data BRG-BAR-4112 (Period 1–24)

Period	Actual
1	140
2	135
3	125
4	105
5	150
6	170
7	190
8	200
9	180
10	150
11	120
12	130
13	170
14	165
15	150
16	130
17	190
18	210
19	240
20	250
21	220
22	190
23	160
24	175

The demand pattern reveals substantial seasonal swings, with demand rising from 105 units (Period 4) to 200 units (Period 8) during the first cycle, and from 130 units (Period 16) to 250 units (Period 20) during the second cycle. The magnitude of increase between annual peaks exceeds 25%, indicating strong upward growth momentum. Despite higher volatility, the timing of seasonal peaks remains stable, confirming deterministic seasonal structure rather than random fluctuation. This consistent seasonal timing across large amplitude variations supports the application of additive decomposition, as the seasonal interval remains constant even when the overall level increases significantly.

The optimal parameter configuration results in MAPE of 3.82%, RMSE of 6.99, MAE of 8.16, and sMAPE of 4.0%, indicating very high forecasting accuracy despite the larger variance of this product.

Table 17. Parameter Tuning Results BRG-BAR-4112

α	β	γ	MAPE	RMSE	MAE	sMAPE
0.99	0.77	0	6.15%	14.94	11.30	6.4%
0.5	0.1	0.4	4.54%	8.87	11.32	4.7%
0.1	0.01	0.15	3.82%	6.99	8.16	4.0%

After optimization, the Holt–Winters model was applied to project demand for the subsequent 12 periods. The forecast results are presented in Table 18.

Table 18. Best Parameter Forecast Results of BRG-BAR-4112 (Period 25–36)

Period	Forecast
25	198.71
26	195.85
27	187.40
28	169.76
29	219.20
30	241.47
31	265.16
32	277.43
33	258.42
34	230.95
35	203.53
36	216.83

The forecast results show a peak demand of 277.43 units in Period 32, continuing the upward trend observed historically. Although demand variability is higher, the model maintains a stable seasonal structure without producing unrealistic spikes.

Figure 5 presents a graphical comparison between historical and forecast demand for BRG-BAR-4112. It shows a comparison of actual data and forecast results using the Holt-Winters method with parameters $\alpha = 0.1$, $\beta = 0.01$, and $\gamma = 0.15$ and a season length of 12 periods. These parameters represent the best tuning results, resulting in the lowest error values.

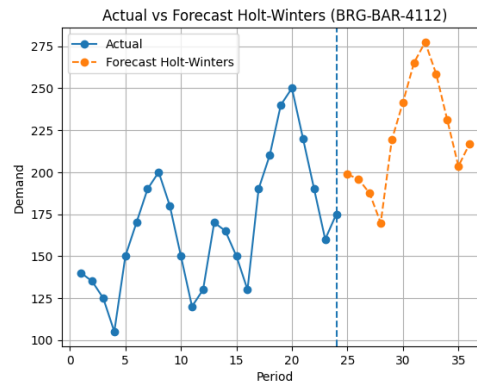


Figure 5. Comparison of Historical and Forecasted Demand for BRG-BAR-4112

Despite higher demand variability, the Holt-Winters model captures the general upward trend and seasonal repetition, demonstrating robustness for high-volume products.

The Holt-Winters model achieves the lowest error across all metrics, confirming its robustness even for high-volume products with large seasonal fluctuations.

Table 19. Comparison of Method Accuracy for BRG-BAR-4112

Method	MAPE	RMSE	MAE	sMAPE
Holt-Winters	3.82%	8.16	6.99	4.0%
Moving Average	5.96%	12.71	9.83	6.2%
Seasonal Naive	9.88%	19.85	15.42	10.2%

3.2. SAW Decision Matrix

Table 20 presents a decision matrix compiled from actual customer orders received during January 4–5, 2026. Each alternative (A1–A7) represents a real customer order that must be evaluated for distribution priority. Four decision criteria are considered: demand forecast (C1), distribution distance (C2), customer priority level (C3), and stock availability (C4). Demand forecast (C1) is derived from the Holt-Winters model and reflects the expected product demand in the upcoming period, thus serving as the primary indicator for determining priority. Distance (C2) represents the logistical effort required for delivery and is treated as a cost criterion. Customer priority (C3) is uniform across all alternatives (value = 1), indicating that all customers belong to

the same priority class in this scenario. Stock availability (C4) reflects the current inventory level, which influences the feasibility and urgency of fulfillment.

Table 20. Decision Matrix presents customer orders received on January 4–5, 2026

Alternative	C1	C2	C3	C4
A1	79.98	199.27	1	191
A2	129.19	107.86	1	33
A3	79.98	17.21	1	191
A4	75.45	17.87	1	931
A5	198.71	90.45	1	44
A6	79.98	16.68	1	191
A7	79.98	63.88	1	191

The matrix in Table 20 represents the raw evaluation stage prior to normalization. The variation across criteria values indicates the need for normalization to ensure comparability across different measurement scales. For instance, A5 shows the highest demand value (198.71), while A6 has the shortest delivery distance (16.68), highlighting potential trade-offs between criteria.

Table 21 presents a second decision scenario based on customer orders received during January 6–7, 2026. In this case, eight alternatives (A1–A8) are evaluated using the same criteria. Compared to the previous dataset, this scenario introduces greater variation in distance (C2), particularly for A5 (386.04), which represents a significantly higher logistical cost.

Table 21. Decision Matrix presents customer orders received on January 6–7, 2026

Alternative	C1	C2	C3	C4
A1	198.71	18.30	1	43
A2	75.45	52.60	1	926
A3	75.45	55.09	1	926
A4	75.45	55.14	1	926
A5	84.62	386.04	1	50
A6	75.45	22.11	1	926
A7	75.45	15.41	1	926
A8	79.98	55.23	1	190

The inclusion of multiple evaluation periods demonstrates the consistency of the proposed decision model under different operational conditions. Similar to Table 20, forecast demand remains the primary benefit criterion, while distance acts as a limiting factor in determining distribution feasibility. The presence of multiple alternatives with similar demand values (e.g., A2–A4, A6–A7) emphasizes the importance of multi-criteria evaluation rather than relying on a single factor.

3.3. Normalization Result.

Table 22 presents the normalized decision matrix for customer orders on January 4–5, 2026. The normalization process transforms all criteria values into a comparable scale between 0 and 1 using benefit and cost normalization formulas. Benefit criteria (C1, C3, C4) are normalized by dividing each value by the maximum value in the column, while the cost criterion (C2) is normalized using the inverse ratio.

Table 22. Normalized Matrix for customer orders received on January 4–5, 2026

Alternative	C1	C2	C3	C4
A1	0.4026	0.0837	1.0000	0.2052
A2	0.6500	0.1546	1.0000	0.0355
A3	0.4026	0.9692	1.0000	0.2052
A4	0.3796	0.9335	1.0000	1.0000
A5	1.0000	0.1844	1.0000	0.0473
A6	0.4026	1.0000	1.0000	0.2052
A7	0.4026	0.2612	1.0000	0.2052

The normalized results highlight the relative performance of each alternative across criteria. For example, A5 achieves the maximum normalized value (1.0000) for demand (C1), indicating the highest priority from a demand perspective. Meanwhile, A6 obtains the highest

normalized score for distance ($C2 = 1.0000$), reflecting the shortest delivery route. A4 stands out with a perfect score in stock availability ($C4 = 1.0000$), indicating strong fulfillment capability.

This transformation ensures that no single criterion dominates the decision unfairly due to scale differences, allowing a balanced evaluation in the subsequent ranking stage.

Table 23 presents the normalized matrix for the second dataset (January 6–7, 2026). Similar normalization procedures are applied to ensure consistency. The results show that A1 achieves the highest normalized value in demand ($C1 = 1.0000$), while A7 achieves the highest score in distance ($C2 = 1.0000$), indicating the most efficient delivery route.

Table 23. Normalized Matrix for customer orders received on January 6–7, 2026

Alternative	C1	C2	C3	C4
A1	1.0000	0.8421	1.0000	0.0464
A2	0.3797	0.2930	1.0000	1.0000
A3	0.3797	0.2797	1.0000	1.0000
A4	0.3748	0.2795	1.0000	1.0000
A5	0.4258	0.0399	1.0000	0.0540
A6	0.3797	0.6970	1.0000	1.0000
A7	0.3797	1.0000	1.0000	1.0000
A8	0.4025	0.2790	1.0000	0.2052

Interestingly, several alternatives (A2–A7) achieve identical values in stock availability ($C4 = 1.0000$), suggesting that inventory is not a limiting factor for these orders. Instead, differentiation among alternatives is primarily driven by demand and distance. This reinforces the importance of multi-criteria aggregation in distinguishing priorities when certain criteria exhibit uniform values.

3.4. Final Ranking Result.

Table 24 presents the final ranking results for customer orders on January 4–5, 2026, obtained through weighted summation of the normalized criteria values. The ranking indicates that A4 achieves the highest final score (0.7385), making it the top priority for distribution. This result is influenced by A4's strong performance in stock availability and relatively high normalized distance score, despite having moderate demand.

Table 24. Final Ranking for customer orders received on January 4–5, 2026

Alternative	Final Score	Rank
A4	0.7385	1
A5	0.6464	2
A6	0.6020	3
A3	0.5958	4
A2	0.4980	5
A7	0.4542	6
A1	0.4187	7

The second-ranked alternative, A5 (0.6464), benefits from having the highest demand value, although its lower stock availability slightly reduces its overall score. Alternatives such as A6 and A3 also achieve competitive rankings due to favorable distance values and balanced performance across criteria.

On the other hand, A1 receives the lowest score (0.4187), primarily due to its relatively long delivery distance and lower comparative advantage in other criteria. These results demonstrate that the SAW method effectively balances multiple criteria and does not rely solely on demand, ensuring more realistic and operationally feasible prioritization.

Table 25 presents the final ranking results for customer orders on January 6–7, 2026. In this scenario, A1 achieves the highest score (0.7777), indicating the highest distribution priority. This result is driven by A1's strong performance across multiple criteria, particularly its maximum demand value and relatively favorable distance.

The second-ranked alternative, A7 (0.7519), achieves a high score due to its optimal distance value, despite having moderate demand. Similarly, A6 also ranks highly due to a balanced combination of criteria.

In contrast, A5 records the lowest score (0.3891), primarily due to its extremely large distance value, which significantly reduces its overall ranking despite moderate demand. This highlights the critical role of distance as a cost criterion in the decision-making process.

Table 25. Final Ranking for customer orders received on January 6–7, 2026

Alternative	Final Score	Rank
A1	0.7777	1
A7	0.7519	2
A6	0.6913	3
A2	0.6105	4
A3	0.6078	5
A4	0.6078	6
A8	0.4578	7
A5	0.3891	8

Overall, the ranking results across both datasets demonstrate that the integration of forecasting outputs with SAW provides a robust and consistent framework for distribution prioritization. The method successfully captures trade-offs between demand, logistics, and resource availability, resulting in practical and data-driven decision support.

3.5. Discussion

The results presented in Section 3.1 demonstrate that the Holt–Winters additive model consistently produces reliable forecasting performance across all evaluated products with different demand characteristics. Based on Tables 7, 11, 15, and 19, the model achieves MAPE values ranging from 3.82% to 7.47%, which fall within the *very accurate* category ($\text{MAPE} < 10\%$). This indicates that the model is capable of capturing both seasonal patterns and trend components effectively, even with a relatively limited dataset of 24 observations.

A key finding is the consistency of the optimal parameter configuration ($\alpha = 0.1$, $\beta = 0.01$, $\gamma = 0.15$) across all products. This suggests that lower smoothing parameters are more suitable for datasets with stable seasonal structures, as they prevent excessive sensitivity to short-term fluctuations while preserving long-term patterns. The relatively low RMSE and MAE values further confirm that forecasting errors remain controlled across different demand scales, including high-volume products such as BRG-BAR-4112.

Importantly, the superiority of the Holt–Winters model is validated through comparison with baseline methods. Across all products, Holt–Winters consistently outperforms Moving Average and Seasonal Naive methods in all evaluation metrics (MAPE, RMSE, MAE, and sMAPE). For example, in Table 7, Holt–Winters achieves a MAPE of 7.25%, compared to 9.12% (Moving Average) and 12.85% (Seasonal Naive). Similar performance gaps are observed in other products, confirming that incorporating both trend and seasonality provides significant accuracy improvement over simpler approaches. This comparison strengthens the validity of the forecasting results and addresses the need for contextual evaluation against baseline models.

The integration of forecasting results into the SAW-based decision-making framework (Section 3.2–3.4) further demonstrates the practical applicability of the proposed approach. By embedding forecasted demand as criterion C1, the prioritization process becomes dynamically aligned with future demand projections rather than relying solely on historical or static data. The ranking results in Tables 24 and 25 show that the highest-priority alternatives are not determined by a single factor, but by a balanced interaction among demand, distance, and stock availability.

For instance, in Table 24, alternative A4 achieves the highest rank (0.7385) despite not having the highest demand, due to its superior stock availability and favorable distance. Conversely, in Table 25, A1 ranks first (0.7777) primarily due to its dominant demand value combined with relatively efficient logistics. These findings confirm that the SAW method effectively captures trade-offs among multiple criteria and produces more operationally realistic prioritization outcomes compared to single-criterion approaches.

Another important observation is that certain criteria may become less discriminative in specific scenarios. For example, customer priority (C3) remains constant across all alternatives, and stock availability (C4) shows identical normalized values for several alternatives in Table 23. In

such cases, differentiation is driven primarily by demand (C1) and distance (C2), highlighting the importance of multi-criteria aggregation in maintaining decision sensitivity.

Despite these strengths, several limitations must be acknowledged. First, the time series dataset consists of only 24 monthly observations, which may limit the stability of seasonal index estimation and reduce generalizability to products with different demand behaviors. Second, the parameter optimization process relies on a simple holdout validation (Periods 13–24), which may introduce bias compared to more robust validation techniques such as rolling-origin evaluation. Third, the SAW evaluation is conducted on a limited number of decision instances (7–8 alternatives per period), without longitudinal testing across multiple operational cycles or comparison with real-world scheduling outcomes.

Overall, the integration of Holt–Winters forecasting and SAW provides a structured and data-driven approach for distribution prioritization. The proposed framework not only improves forecasting accuracy but also enhances decision-making transparency and adaptability, making it suitable for practical implementation in supply chain and distribution management contexts.

Building upon these findings, this study contributes by (1) integrating time-series forecasting with multi-criteria decision-making in a unified framework, (2) incorporating forecasted demand dynamically as a decision criterion, and (3) validating the proposed approach using real operational data across multiple products. These contributions distinguish this work from conventional approaches that treat forecasting and decision-making as separate processes.

4. CONCLUSION

This study developed and validated an integrated decision support framework combining Holt–Winters Exponential Smoothing (HWES) and Simple Additive Weighting (SAW) for distribution priority optimization at CV. Citra Nalar Teknologi. The additive HWES model demonstrated consistently high forecasting accuracy, achieving MAPE values ranging from 3.82% to 7.47%, supported by relatively low RMSE, MAE, and sMAPE across four representative products. These results confirm the model’s capability to capture both seasonal patterns and trend components in multi-product demand data. Furthermore, comparative evaluation shows that Holt–Winters outperforms baseline methods, including Moving Average and Seasonal Naive, across all accuracy metrics. This highlights the importance of incorporating both trend and seasonality to improve forecasting performance. The integration of forecasted demand as a primary criterion within the SAW model enabled a structured and demand-driven prioritization process. The model was evaluated using two sets of actual customer orders (January 4–5 and January 6–7, 2026), demonstrating consistent ranking behavior under different operational conditions. The results indicate that distribution priority is determined through a balanced evaluation of forecast demand, delivery distance, and stock availability, rather than reliance on a single dominant factor. Overall, the proposed framework enhances decision consistency, transparency, and analytical rigor in distribution planning. This study contributes by systematically linking time series forecasting with multi-criteria decision-making in an integrated workflow. Future research may extend this work by incorporating larger datasets, more robust validation techniques, adaptive weighting schemes, and logistics optimization models to further improve real-world applicability.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The data associated with this study are confidential due to commercial privacy and are not publicly available, but can be requested from the corresponding author upon reasonable request.

AUTHOR CONTRIBUTIONS

Muhammad Rohman Irsyadi: Conceptualization; Data Curation; Methodology; Software; Visualization; Writing - Original Draft. **Mohammad Idhom:** Conceptualization; Methodology; Supervision; Writing - Review & Editing. **Afina Lina Nurlaili:** Methodology; Supervision; Writing - Review & Editing.

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