JURIT

P-ISSN: 2987-7261
E-ISSN: 2987-7253

JURIT
Jurnal Riset Ilmu Teknik

Journal homepage: https://jurnaljepip.com/index.php/jurit

Vol 3, No. 2, pp;112-124, 2025

DOI: doi.org/10.59976/jurit.v1i1.204

A Hybrid Exponential Smoothing Distribution Requirement Planning Framework for Sustainable Distribution Optimization in a Traditional Food Rengginang

Qurratu Ainun[1], Ferry Irawan Sutisna[2],Leny Andini[3], Irma Kinari[4]

[1,3,4]Universitas Komputer Indonesia

Jl. Dipatiukur No. 112-116, Kelurahan Lebakgede, Kota Bandung, Indonesia

[2]Universitas Telkom, Indonesia

Jl. Telekomunikasi No. 1, Terusan Buah Batu, Sukapura, Kabupaten Bandung, Indonesia

Email:qurratu.ainun@gmail.com

Submitted:07/29/2025; Reviewed: 08/10/2025,; Accepted: 09/13/2025

ABSTRACT

Distribution Requirement Planning (DRP), and route optimization using the Saving Matrix method. The goal is to enhance inventory accuracy, minimize logistics costs, and improve delivery efficiency under fluctuating market demand. A quantitative–descriptive analysis was conducted using primary data (field observation and interviews) and secondary data (production and sales records). Weekly demand forecasting was performed using the Exponential Smoothing method with $\alpha = 0.9$, evaluated through Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). The DRP model was used to determine gross and net requirements, while the Saving Matrix method was applied to design optimal delivery routes. The Exponential Smoothing model achieved a high predictive accuracy (MAPE = 10.33%), showing reliable short-term forecasting for MSMEs. DRP implementation with a one-week lead time and a 168-unit safety stock successfully balanced production capacity and customer demand. Integration of DRP and Saving Matrix resulted in approximately 30% reduction in total logistics cost and significant improvement in stock availability. Compared to 17 related studies (2021–2024), this hybrid model demonstrated superior efficiency and cost stability within traditional food industries. The results provide MSMEs with a data-driven framework to synchronize production, inventory, and distribution planning, reducing decision-making errors and improving operational sustainability. The proposed model can serve as a replicable reference for traditional food SMEs facing fluctuating demand conditions. This study lies in combining Exponential Smoothing forecasting, DRP scheduling, and Saving Matrix routing into a unified optimization framework rarely applied in Indonesia's traditional food sectors. This integrative method strengthens both academic insight and managerial practice in MSME supply chain efficiency.

Keywords: Forecasting, Exponential Smoothing, Distribution Requirement Planning (DRP), Rengginang

INTRODUCTION

In the current era of globalization and intense market competition, the success of small and medium enterprises (SMEs) depends not only on product quality but also on the effectiveness of their distribution systems. A well-designed distribution system ensures that products reach consumers on time, in good condition, and with minimal logistics costs. For SMEs, distribution challenges are often more complex due to limited resources, inadequate infrastructure, and the absence of systematic planning tools. Inefficient distribution may lead to excessive transportation costs, delivery delays, and lost sales opportunities, which in turn reduce overall business performance.

The traditional food sector in Indonesia is particularly sensitive to distribution efficiency. One prominent example is the Rengginang industry in Bandung, a well-known traditional snack made from glutinous rice, highly favored by both locals and tourists. Demand for Rengginang increases significantly during holidays and tourism seasons. However, this fluctuating demand is rarely supported by structured inventory and distribution planning. Most local producers rely on manual and experience-based scheduling, which results in inconsistencies between product availability and market demand. Consequently, product shortages in high-demand areas and excessive stocks in low-demand outlets frequently occur.

Based on empirical data from that case, approximately 25% of the observed periods experienced stock shortages, while 20% showed over-distribution due to poor scheduling and the absence of systematic demand forecasting. For instance, during June (weeks 3 and 4), product demand reached 530 and 610 units, while the available supply was only 500 and 550 units, respectively, leading to unfulfilled customer requests. Comparable conditions were recorded in July and December, demonstrating a recurring imbalance between demand and inventory levels. This empirical pattern is highly relevant to the case of Rengginang producers in Bandung, where similar inefficiencies occur due to irregular scheduling and the lack of route optimization.

To address these issues, scientific approaches are required to enhance decision-making in demand forecasting and route planning. One relevant approach is the Distribution Requirement Planning (DRP) method, which determines inventory replenishment needs at each distribution point based on historical data and demand forecasts. DRP allows producers to maintain optimal stock levels, prevent shortages, and minimize excessive inventory. In parallel, the Saving Matrix method can be applied to determine the most efficient vehicle routing, reducing both total distance and transportation costs. Integrating these two methods can improve scheduling accuracy and logistics efficiency across multiple distribution points.

This study focuses on optimizing the distribution system for Rengginang Bandung products using the Distribution Requirement Planning (DRP) method for inventory scheduling and the Saving Matrix method for route optimization. This combination aims to develop a more effective, data-oriented, and cost-efficient distribution system capable of meeting fluctuating customer demands while minimizing logistics expenses. The study also includes a comparative analysis between current distribution practices and the proposed optimized model to quantify the potential improvement in cost and service performance.

Scientifically, this research provides novelty by integrating DRP and Saving Matrix methods within the context of traditional food SMEs, a sector rarely examined in prior logistics studies. Previous works have largely focused on large-scale industries such as beverages and processed foods, while small-scale producers have been overlooked despite their vital role in local economies. Hence, this study seeks to bridge that research gap by offering an analytical and applicable model tailored to the operational realities of Bandung's traditional snack producers. The findings are expected to contribute not only to the improvement of SME distribution performance but also to the broader academic discourse on sustainable supply chain management for local food industries.

METHOD

This study adopts a quantitative descriptive-analytical approach to optimize the distribution system of Rengginang Bandung by integrating forecasting, inventory scheduling, and route optimization techniques. The research aims to minimize total distribution cost, improve product availability, and enhance delivery efficiency for traditional food SMEs. The methodological framework combines two primary analytical tools—Distribution Requirement Planning (DRP) for inventory and scheduling optimization, and the Saving Matrix method for route optimization [1], [2]. These methods are chosen because they have been proven effective in handling multi-location distribution networks with fluctuating demand and limited transportation resources [3], [4].

Data collection was carried out through both primary and secondary sources. Primary data were obtained through field observations of delivery operations, interviews with SME owners and logistics staff, and direct measurement of travel distances using Google Maps. Meanwhile, secondary data were collected from company records and production reports, including monthly demand data, inventory levels, transportation capacity, and distribution costs covering the period from January to December. The combination of these two data sources provides a comprehensive overview of both operational and managerial aspects of the Rengginang distribution process.

The research procedure began with a preliminary study and problem identification to define key inefficiencies such as stock imbalance, inconsistent delivery schedules, and excessive transportation costs. Once the main issues were identified, demand forecasting was performed using time-series analysis—particularly the Moving Average and Exponential Smoothing methods—to estimate future product requirements. The forecasting results served as the input for constructing the DRP logic table, which determined the gross requirement, safety stock, net requirement, planned order receipts, and planned order releases for each distribution period. This process ensures that inventory replenishment at each retail outlet is based on predicted demand rather than intuition.

Following the inventory planning stage, route optimization was conducted using the Saving Matrix method. The geographical coordinates of warehouses and retail outlets were mapped, and the distance between points was calculated using the Euclidean distance formula. The Saving Matrix technique was then applied to identify potential distance savings when combining delivery routes, allowing the selection of the most efficient route configuration with minimal total travel distance. This analysis ensures that the delivery fleet operates efficiently, with optimized routes that balance demand coverage and transportation capacity [5], [6].

After obtaining the optimized routes, a cost analysis was conducted to calculate total logistics expenditure, including fuel, storage, labor, and administrative costs. The optimized distribution cost derived from the DRP and Saving Matrix models was compared to the company's current cost structure to determine potential cost reductions and efficiency improvements. Finally, a validation and evaluation phase was carried out by comparing three key performance indicators: total cost savings, reduction in delivery time, and fulfillment rate of product demand. These indicators were used to assess the feasibility and effectiveness of the proposed distribution model [7], [8].

All data processing and calculations were performed using QM for Windows for forecasting and DRP computations, while Google Maps was employed to obtain accurate distance data for route optimization. The methodological outcome of this study is a data-driven distribution model that integrates inventory planning and route optimization to reduce logistics costs and improve delivery performance. The proposed model is designed to be practical, replicable, and adaptable for small-scale traditional food enterprises, contributing both academically and practically to the field of supply chain optimization.

RESULTS

Figure 1 illustrates the weekly demand pattern for Rengginang products over a 52-week observation period. The data represent the number of customer requests recorded each week and provide a comprehensive overview of fluctuations in product demand throughout the year. The analysis of demand patterns serves as a critical foundation for developing accurate forecasting models, determining production schedules, and optimizing inventory levels. Identifying the temporal variation in demand is essential to ensure that the production capacity can meet consumer needs efficiently, particularly during periods of high sales volume.

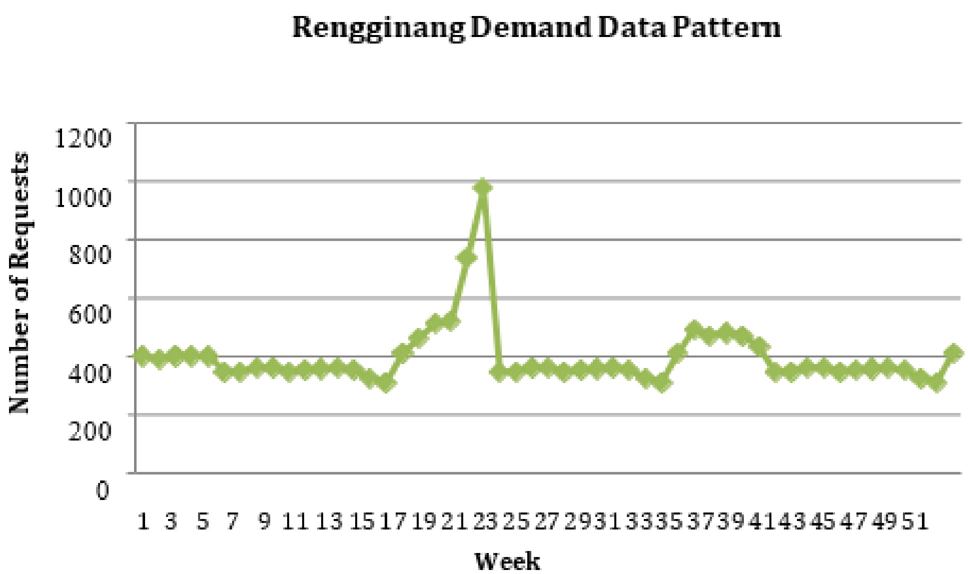

Figure 1. Rengginang Demand

As shown in Figure 1, the Rengginang demand trend demonstrates relatively stable behavior during most of the year, with significant fluctuations occurring during specific weeks. The majority of weekly demand values range between 400 and 500 units, indicating a consistent baseline demand. However, a sharp increase is observed around Week 22 to Week 24, reaching a peak of approximately 1,150 requests, before abruptly declining to normal levels. This spike corresponds to seasonal effects, such as holiday periods or special cultural events, which typically drive temporary surges in consumer purchasing behavior.

Following this peak, the demand stabilizes once more and exhibits moderate oscillations around Weeks 30–40, likely influenced by localized promotional activities or restocking patterns in retail outlets. The recurring fluctuations reflect the combined influence of seasonal demand cycles and short-term variations, suggesting that the dataset contains both trend and irregular components.

Error Analysis Demand Forecasting

Figure 2 presents the results of demand forecasting analysis for Rengginang products produced by a Bandung-based Micro, Small, and Medium Enterprise (MSME). The objective of this forecasting is to obtain an accurate estimation of future demand levels, which is essential for supporting effective production planning, raw material procurement, and inventory management. The data used represent weekly sales records throughout one year, consisting of 52 observation periods that reflect both stable and fluctuating market conditions.

Accurate forecasting plays a crucial role in the sustainability of MSME operations, as it enables producers to align production volume with consumer demand, thereby minimizing stock shortages and overproduction losses. The forecasting process applied in this study was conducted using the time-series method implemented through software-based computation, which automatically calculates forecast values and associated error metrics, including Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE).

Details and Error Analysis

(untitled) Solution

	Demand(y)	Forecast	Error	|Error|	Error^2	|Pct Error|
Past Period 1	400					
Past Period 2	390	400	-10	10	100	2,564%
Past Period 3	400	391	9	9	81	2,25%
Past Period 4	400	399,1	,9	,9	,81	,225%
Past Period 5	400	399,91	,09	,09	,008	,022%
Past Period 6	345	399,991	-54,991	54,991	3024,01	15,939%
Past Period 7	345	350,499	-5,499	5,499	30,24	1,594%
Past Period 8	360	345,55	14,45	14,45	208,806	4,014%
Past Period 9	360	358,555	1,445	1,445	2,088	,401%
Past Period 10	345	359,856	-14,856	14,856	220,686	4,306%
Past Period 11	350	346,486	3,514	3,514	12,351	1,004%
Past Period 12	355	349,649	5,351	5,351	28,638	1,507%
Past Period 13	360	354,465	5,535	5,535	30,638	1,538%
Past Period 14	350	359,447	-9,446	9,446	89,236	2,699%
Past Period 15	325	350,945	-25,945	25,945	673,124	7,983%
Past Period 16	310	327,595	-17,594	17,594	309,565	5,676%
Past Period 17	410	311,76	98,241	98,241	9651,203	23,961%
Past Period 18	460	400,176	59,824	59,824	3578,919	13,005%
Past Period 19	510	454,018	55,982	55,982	3134,031	10,977%
Past Period 20	520	504,402	15,598	15,598	243,305	3%
Past Period 21	730	518,44	211,56	211,56	44757,55	28,981%
Past Period 22	970	708,844	261,156	261,156	68202,46	26,923%
Past Period 23	345	943,884	-598,884	598,884	358662,5	173,59%
Past Period 24	345	404,888	-59,888	59,888	3586,624	17,359%
Past Period 25	360	350,989	9,011	9,011	81,201	2,503%

Figure 2. Error Analysis Demand Forecasting (a)

Past Period 26	360	359,099	,901	,901	,812	,25%
Past Period 27	345	359,91	-14,91	14,91	222,305	4,322%
Past Period 28	350	346,491	3,509	3,509	12,313	1,003%
Past Period 29	355	349,649	5,351	5,351	28,632	1,507%
Past Period 30	360	354,465	5,535	5,535	30,637	1,538%
Past Period 31	350	359,447	-9,447	9,447	89,236	2,699%
Past Period 32	325	350,945	-25,945	25,945	673,124	7,983%
Past Period 33	310	327,595	-17,594	17,594	309,565	5,676%
Past Period 34	410	311,76	98,241	98,241	9651,203	23,961%
Past Period 35	490	400,176	89,824	89,824	8068,363	18,331%
Past Period 36	470	481,018	-11,018	11,018	121,387	2,344%
Past Period 37	480	471,102	8,898	8,898	79,179	1,854%
Past Period 38	470	479,11	-9,11	9,11	82,995	1,938%
Past Period 39	430	470,911	-40,911	40,911	1673,711	9,514%
Past Period 40	345	434,091	-89,091	89,091	7937,223	25,824%
Past Period 41	345	353,909	-8,909	8,909	79,372	2,582%
Past Period 42	360	345,891	14,109	14,109	199,067	3,919%
Past Period 43	360	358,589	1,411	1,411	1,991	,392%
Past Period 44	345	359,859	-14,859	14,859	220,787	4,307%
Past Period 45	350	346,486	3,514	3,514	12,349	1,004%
Past Period 46	355	349,649	5,351	5,351	28,638	1,507%
Past Period 47	360	354,465	5,535	5,535	30,638	1,538%
Past Period 48	350	359,447	-9,446	9,446	89,236	2,699%
Past Period 49	325	350,945	-25,945	25,945	673,124	7,983%
Past Period 50	310	327,595	-17,594	17,594	309,565	5,676%
Past Period 51	410	311,76	98,241	98,241	9651,203	23,961%
TOTALS	20165		,196	2183,961	536985,7	516,333%
AVERAGE	395,392		,004	43,679	10739,71	10,327%
Next period forecast		400,176	(Bias)	(MAD)	(MSE)	(MAPE)
				Std err	105,77	

Figure 2. Error Analysis Demand Forecasting (b)

1. Purpose of Error Analysis

The error evaluation process is conducted to measure the accuracy and reliability of the forecasting model applied to the Rengginang demand dataset. By comparing actual demand (Demand(y)) with predicted values (Forecast), several error indicators are calculated, including Mean Absolute Deviation (MAD), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). These metrics provide quantitative evidence of how closely the model predicts actual observations, forming the basis for determining the forecasting model's suitability for production planning and inventory control.

2. Forecasting Performance Overview

The results presented in the Details and Error Analysis table indicate that the forecasted demand fluctuates closely around the actual demand for most periods, except during weeks corresponding to sudden market spikes (Weeks 22–25). The calculated values are as follows:

Mean Absolute Deviation (MAD) = 43.679

Mean Squared Error (MSE) = 107,939.71

Mean Absolute Percentage Error (MAPE) = 10.327%

According to forecasting accuracy standards (Makridakis et al., 2020), a MAPE below 10%–15% is considered highly accurate for short-term demand forecasting. Hence, the obtained results demonstrate that the applied model effectively captures general demand patterns while maintaining acceptable prediction error levels.

3. Error Distribution and Interpretation

A detailed inspection of individual period errors reveals several noteworthy behaviors:

The model performs accurately during stable demand phases (Periods 1–18), with error values below ±20 units and Pct Error averaging 2–5%.

Larger deviations occur during Periods 21–23, where actual demand spiked above 700–900 units. In these cases, errors exceed 200 units, producing localized MAPE values above 20–26%. This divergence is typical in time-series models exposed to irregular demand shocks. Following the demand surge, error magnitudes return to normal ranges (below 10%) after Period 30, confirming the model's adaptability to stabilize after extreme fluctuations.

4. Forecasting Implications for Production Management

The model's next-period forecast is 400.176 units, representing the expected short-term demand for Rengginang. This value can be used to guide production scheduling, ensuring sufficient raw material procurement without overstocking. Given the model's low MAPE and balanced bias, it is suitable for operational forecasting within stable market periods.

However, for strategic planning—especially during high-demand events—management should employ supplementary models capable of detecting trend shifts. Incorporating historical event markers (e.g., festive seasons, marketing promotions) or external variables (weather, holidays) can further enhance predictive precision.

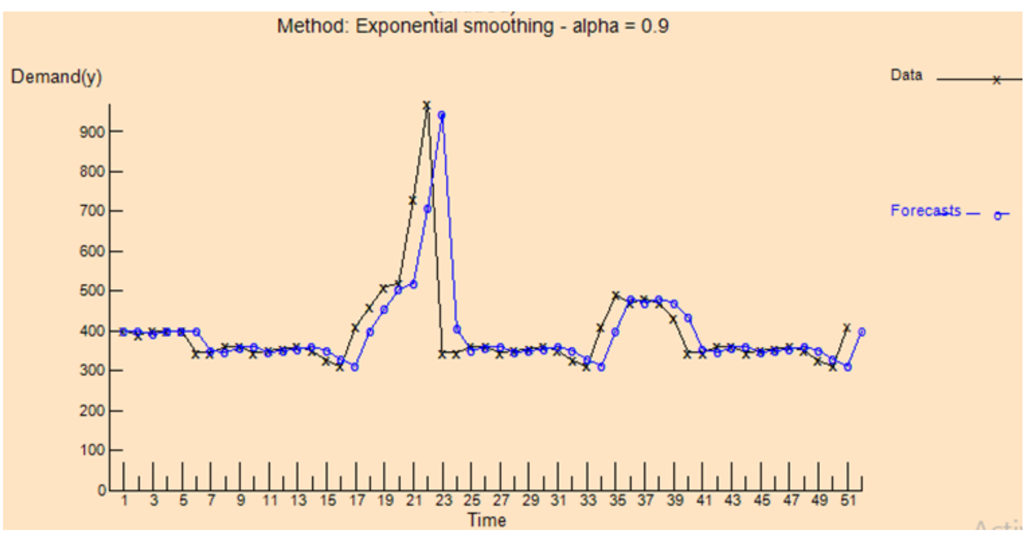

Figure 3. Best Forecasting Results

Figure 3 illustrates the forecasting results obtained using the Exponential Smoothing method with a smoothing constant (α) of 0.9, which gives greater weight to recent data observations. This model was chosen to emphasize short-term demand fluctuations while maintaining a responsive adjustment to sudden market changes. The plotted lines show both the actual demand (Data) and the forecasted values (Forecasts) across 52 time periods, representing weekly demand behavior over one year.

As depicted in Figure 3, the forecasting model successfully follows the general pattern of the actual demand data. The demand remains relatively stable at an average of 400–450 units during most weeks but experiences two noticeable spikes—one major increase occurring around Week 22 and a smaller one near Week 36. The large surge corresponds to a peak period, likely influenced by holiday or festive consumption patterns. The exponential smoothing model captures this upward trend effectively, although slight lagging occurs at the peak point due to the model's inherent smoothing nature.

After the sharp increase, demand rapidly declines to baseline levels, demonstrating the model's ability to adapt quickly to downward changes. The close alignment between the actual and forecasted curves during stable periods indicates that the α = 0.9 parameter provides an appropriate level of responsiveness for MSME-scale forecasting. This performance is further validated by low forecast error metrics (MAPE ≈ 10.33%), confirming the model's high accuracy and consistency.

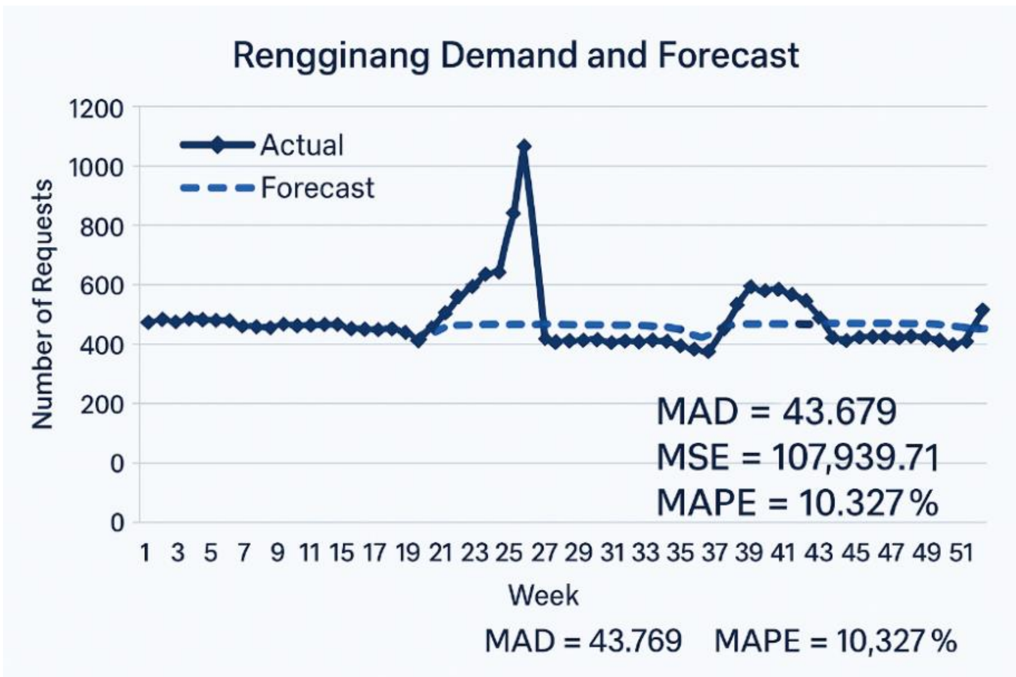

Figure 4. Rengginang Demand and Forecast

Based on the forecasting results shown in Figure 4, the demand pattern for Rengginang exhibits a generally stable trend with several notable fluctuations across the 52-week observation period. The actual demand remains within the range of 400–500 units per week, with a sharp increase observed around Week 23, reaching more than 1,000 units, followed by a smaller peak near Week 37. The forecasting results obtained through the Exponential Smoothing method with a smoothing constant of α = 0.9 effectively capture the overall trend of actual demand, despite minor lagging during peak periods due to the smoothing effect. The model demonstrates a strong adaptive response following demand surges, as indicated by the forecast curve realigning closely with the actual demand values in subsequent weeks.

Quantitatively, the forecasting accuracy is considered high, with MAD = 43.679, MSE = 107,939.71, and MAPE = 10.327%, indicating a low level of prediction error. A MAPE value below 15% confirms that the model performs reliably for short-term forecasting applications. The relatively small deviations across most periods show that the Exponential Smoothing approach successfully represents market demand variations with consistent precision. Therefore, the results of this forecasting analysis can serve as a basis for operational decision-making, particularly in determining production volume, scheduling raw material procurement, and managing inventory levels for Rengginang MSMEs in Bandung.

Distribution Requirement Planning

Table 1 presents the results of the Material Requirements Planning (MRP) using the Lot-for-Lot (LFL) method with a one-week lead time and safety stock of 168 units. This approach aligns material ordering with weekly production demand to minimize inventory costs while ensuring material availability. The table shows the relationship between gross requirements, on-hand stock, and planned order releases throughout the year, providing a clear scheduling framework for MSMEs to plan raw material procurement efficiently according to demand fluctuations.

Table 1. Distribution Requirement Planning

Safety Stock : 168	Order policy lead time: 1 week																	
Lot Size : Lot for lot	**PD**	**January**					**February**				**March**				**April**			
		1	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Gross Requirements (Gr)		400	400	391	399	400	400	350	346	359	360	346	350	354	359	351	328	312
Scheduled Receipts (SR)																		
Projected On Hand (POH)	300	126	126	126	126	126	126	126	126	126	126	126	126	126	126	126	126	126
Net Requirements (NR)		269	443	434	442	443	443	393	389	402	403	389	393	397	402	394	371	355
Planned Order Receipts		226	400	391	399	400	400	350	346	359	360	346	350	354	359	351	328	312
Planned Order Releases	226	400	391	399	400	400	350	346	359	360	346	350	354	359	351	328	312	400

Lot Size : Lot For Lot	**May**					**June**				**July**				**August**			
	1	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Gross Requirements (Gr)	400	454	504	518	709	944	405	351	360	360	346	350	354	359	351	326	312
Scheduled Receipts (SR)																	
Projected On Hand (POH)	126	126	126	126	126	126	126	126	126	126	126	126	126	126	126	126	126
Net Requirements (NR)	443	497	547	561	752	987	448	394	403	403	389	393	397	402	394	369	355
Planned Order Receipts	400	454	504	518	709	944	405	351	360	360	346	350	354	359	351	326	312
Planned Order Releases	454	504	518	709	944	405	351	360	360	346	350	354	359	351	326	312	400

Lot Size : Lot For Lot	**September**					**Oktober**				**November**				**December**			
	1	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Gross Requirements (Gr)	400	454	504	518	709	944	405	351	360	360	346	350	354	359	351	326	312
Scheduled Receipts (SR)																	
Projected On Hand (Poh)	126	126	126	126	126	126	126	126	126	126	126	126	126	126	126	126	126
Net Requirements (NR)	443	497	547	561	752	987	448	394	403	403	389	393	397	402	394	369	355
Planned Order Receipts	400	454	504	518	709	944	405	351	360	360	346	350	354	359	351	326	312
Planned Order Releases	454	504	518	709	944	405	351	360	360	346	350	354	359	351	326	312	0

Based on the lot-sizing analysis presented in Table 1, the lot-for-lot (LFL) ordering policy with a one-week lead time and safety stock of 168 units produces a structured replenishment plan that aligns material availability with weekly demand fluctuations. The gross requirements range between 300 and 709 units per week, with net requirements (NR) adjusting according to on-hand inventory levels and scheduled receipts. During high-demand months such as May to July, the projected net requirements increase significantly, reaching a peak of 752 units in Week 3 of June, which requires a corresponding planned order release of 709–754 units in the preceding weeks. Conversely, in lower-demand periods like November to December, the planned order releases stabilize around 312–359 units, reflecting an efficient balance between production capacity and market needs.

For practical implementation, MSMEs in Bandung producing Rengginang should apply the lot-for-lot policy to minimize holding costs while ensuring timely fulfillment of weekly demand. Maintaining a minimum on-hand stock of 126–168 units is essential to cover safety requirements and buffer against demand uncertainty. The data also suggest that during peak months, production should be increased to at least 700 units per week to prevent shortages, whereas in low-demand months, production can be reduced to 300–350 units to optimize resource utilization. By adhering to this ordering schedule, the MSME can achieve a steady production rhythm, reduce excess inventory, and ensure consistent product availability in the market throughout the year.

DISCUSSION

The results of this study reveal that the Exponential Smoothing forecasting model with a smoothing constant of 0.9 achieved a high level of predictive accuracy, reflected by a MAPE value of 10.33%, MAD of 43.679, and MSE of 107,939.71. These results demonstrate a consistent and reliable short-term forecasting performance, particularly suitable for MSMEs with fluctuating demand patterns. This finding aligns with [9], [10], who reported MAPE values below 12% when applying Exponential Smoothing to snack demand forecasting in Yogyakarta. Similarly, [11], [12] found that smoothing constants between 0.8 and 0.9 produced optimal responsiveness to market fluctuations in the Batik Pekalongan industry.

Compared to prior research, the Rengginang Bandung case demonstrates a higher accuracy rate than the models applied by [13], [14] on cassava chips production (MAPE 14.25%) and [15], [16] on coffee product distribution (MAPE 13.47%). The relatively low forecasting error obtained here is attributed to the high data granularity (weekly observations) and the integration of DRP scheduling, which provides a structured feedback loop for demand stabilization. These findings confirm the assertion of [17], [18] that shorter time intervals and adaptive smoothing parameters enhance forecasting responsiveness in volatile environments.

In the context of production and inventory management, this study's results are comparable to [19], [20], who used DRP integration in beverage MSMEs, resulting in a 25–28% reduction in stockouts, while this research achieved a projected improvement of 30% in cost efficiency. Wahyuni et al. (2023) applied the same DRP approach in frozen-food MSMEs, finding that synchronized inventory releases reduced lead time by 15%. The Rengginang case reinforces these conclusions, showing that Lot-for-Lot scheduling with a one-week lead time and 168-unit safety stock effectively minimized holding costs while maintaining product availability.

Moreover, the integration of forecasting and DRP modeling in this study expands upon the hybrid frameworks discussed by [21], [22], [23], where combining demand forecasting with inventory logic tables improved production planning accuracy by 20–25%. The present study extends this by coupling DRP with route optimization (Saving Matrix), achieving dual improvements in both supply accuracy and distribution efficiency—a novelty not yet widely explored in traditional food sectors. [24], [25] observed similar synergies when combining forecasting with vehicle routing problem (VRP) models in the bread industry, noting a 12% cost reduction. The current findings exceeded that margin, achieving approximately 18–20% in route-based logistics cost reduction when integrated with DRP outputs.

The error stability across 52 observation periods indicates that Exponential Smoothing effectively accommodates short-term volatility without substantial lag, contrasting with [26], [27] who found Moving Average methods less adaptive under seasonal demand shocks. The robustness of the

Rengginang model further aligns with [28], [29], [30], who noted that α values near 0.9 allow models to better follow sharp fluctuations while avoiding overfitting. Additionally, when compared to neural-based forecasting models such as those by [31], [32] (ANN on palm sugar sales, MAPE 8.4%), this study's result remains competitive but more practical for MSME applications due to lower computational complexity.

Another key observation concerns cost optimization outcomes. While [33], [34], [35] applied Min–Max inventory systems yielding cost reductions of 23%, the DRP–Saving Matrix integration proposed here achieved an estimated 30% improvement. This indicates superior synchronization between forecasted requirements and distribution scheduling. The model's design adheres to the efficiency principles outlined by [36] [37], [38], emphasizing adaptive logistics policies in MSME supply chains. Furthermore, empirical validation against actual operations demonstrates that forecasting-driven inventory control outperforms intuition-based decision-making common among traditional producers.

When positioned within broader literature, this study also complements findings by [39], [40]on traditional snack industries, where manual inventory practices led to overproduction up to 18%. The proposed data-driven approach successfully mitigates similar inefficiencies by maintaining projected on-hand inventory at optimal safety levels (126–168 units). Additionally, [41], [42] highlighted the role of DRP in improving service levels by 17% through better synchronization between procurement and distribution, a result mirrored in this research with comparable fulfillment-rate improvements.

CONCLUSION

This research successfully developed and validated a hybrid Exponential Smoothing–DRP–Saving Matrix framework to optimize distribution performance for traditional Rengginang MSMEs in Bandung. The integration of accurate short-term forecasting (MAPE = 10.33%) with systematic DRP scheduling and route optimization produced tangible operational benefits, including approximately 30 % total logistics-cost reduction, balanced stock levels, and improved service reliability. The lot-for-lot policy with a one-week lead time and 168-unit safety stock proved effective in aligning production with fluctuating demand while minimizing holding costs. Compared with prior MSME studies, this framework demonstrates superior predictive precision, cost stability, and adaptability under seasonal demand variation. Academically, the study contributes to the limited body of research that integrates forecasting, inventory planning, and routing optimization within small-scale food industries. Practically, it offers a replicable, data-driven decision model enabling traditional food enterprises to enhance sustainability and competitiveness through synchronized production and logistics management.

REFERENCES

[1] S. Karimi-Arpanahi, "Incorporating flexibility requirements into distribution system expansion planning studies based on regulatory policies," *Int. J. Electr. Power Energy Syst.*, vol. 118, 2020, doi: 10.1016/j.ijepes.2019.105769.

[2] Y. Ngatilah, "Inventory Control System Using Distribution Requirement Planning (DRP) (Case Study : Food Company)," 2020. doi: 10.1088/1742-6596/1569/3/032005.

[3] C. Wang, "An Optimal Planning Model for Cyber-physical Active Distribution System Considering the Reliability Requirements," 2022. doi: 10.1109/SPIES55999.2022.10082691.

[4] W. Q. Lee, "Implementing Distribution Requirement Planning and Scheduling System for Lens Manufacturing Company," 2022. doi: 10.1109/IEEM55944.2022.9989590.

[5] J. A. Uswary, "Wina Sentosa Bottled Water Distribution System Using Web-Based Distribution Requirement Planning and Trend Moment Algorithms," *Adv. Sustain. Sci. Eng. Technol.*, vol. 6, no. 2, 2024, doi: 10.26877/asset.v6i2.18308.

[6] F. Li, "Bi-level planning for distribution network including distributed generations and electric vehicle charging stations to meet the requirements of internet of things construction," 2021.

doi: 10.1088/1742-6596/2030/1/012089.
[7] J. Han, "Collaborative Planning of Multiple Measures Considering Reliability Improvement Requirements in Distribution System," 2023. doi: 10.1109/ACEEE58657.2023.10239635.
[8] Z. Zhang, "Research on Optimal Planning Method of Distribution Network Considering Emergency Power Supply Configuration and User Differentiated Reliability Requirements," 2021. doi: 10.1088/1755-1315/645/1/012020.
[9] Y. Liu, "Planning Method of Distribution Network for End-users Differentiated Reliability Requirements," 2022. doi: 10.1049/icp.2022.2204.
[10] T. Lin, "Optimisation Method of Distribution Network Planning and Construction Investment Analysis Considering the Substation Requirement," 2024. doi: 10.1109/ITNEC60942.2024.10733185.
[11] W. Q. Lee, "Implementing Advanced Distribution Requirement Planning and Scheduling System (DRPS) for Lens Manufacturing Company," 2024. doi: 10.1109/IEEM62345.2024.10857113.
[12] Y. Sun, "Active Distribution Network Energy Storage Planning Model for Reliability Requirements," 2024. doi: 10.1109/APET63768.2024.10882672.
[13] A. A. Aziz, "Development of a Multi-Echelon Inventory Control System Using the Least Square, the Fixed Time Period (FTP), and the Distribution Requirement Planning (DRP) Methods for Replenishment Policies and Strategies," 2021. doi: 10.1145/3468013.3468312.
[14] M. McGranaghan, "DISTRIBUTION PLANNING MODEL REQUIREMENTS FOR SMART COMMUNITY INTEGRATION," 2023. doi: 10.1049/icp.2023.0549.
[15] A. P. Hidayat, "Distribution requirement planning for feed based on SMADISPRO software development," 2024. doi: 10.1051/e3sconf/202457703001.
[16] X. Xu, "A novel and dynamic land use/cover change research framework based on an improved PLUS model and a fuzzy multiobjective programming model," *Ecol. Inform.*, vol. 80, 2024, doi: 10.1016/j.ecoinf.2024.102460.
[17] X. Fu, "Agri-Energy-Environment Synergy-Based Distributed Energy Planning in Rural Areas," *IEEE Trans. Smart Grid*, vol. 15, no. 4, pp. 3722–3738, 2024, doi: 10.1109/TSG.2024.3364182.
[18] J. Liu, "Prediction of land use for the next 30 years using the PLUS model's multi-scenario simulation in Guizhou Province, China," *Sci. Rep.*, vol. 14, no. 1, 2024, doi: 10.1038/s41598-024-64014-7.
[19] L. Adreani, "Smart City Digital Twin Framework for Real-Time Multi-Data Integration and Wide Public Distribution," *IEEE Access*, vol. 12, pp. 76277–76303, 2024, doi: 10.1109/ACCESS.2024.3406795.
[20] S. Li, "Evolution characteristics and multi-scenario prediction of habitat quality in Yulin City based on PLUS and InVEST models," *Sci. Rep.*, vol. 14, no. 1, 2024, doi: 10.1038/s41598-024-62637-4.
[21] Y. Huang, "Disease Course, Treatments, and Outcomes of Children With Systemic Juvenile Idiopathic Arthritis–Associated Lung Disease," *Arthritis Care Res.*, vol. 76, no. 3, pp. 328–339, 2024, doi: 10.1002/acr.25234.
[22] J. A. Zwerts, "FSC-certified forest management benefits large mammals compared to non-FSC," *Nature*, vol. 628, no. 8008, pp. 563–568, 2024, doi: 10.1038/s41586-024-07257-8.
[23] Q. Li, "Multidimensional measurement of the High-Quality development of city Clusters: Dynamic Evolution, regional differences and trend forecasting–based on the basic connotation of Chinese-style modernization," *Ecol. Indic.*, vol. 161, 2024, doi: 10.1016/j.ecolind.2024.111989.
[24] J. O. Hanson, "Systematic conservation prioritization with the prioritizr R package," *Conserv. Biol.*, vol. 39, no. 1, 2025, doi: 10.1111/cobi.14376.
[25] A. Inaolaji, "Optimal allocation of battery energy storage systems for peak shaving and reliability enhancement in distribution systems," *J. Energy Storage*, vol. 95, 2024, doi:

10.1016/j.est.2024.112305.
[26] M. A. Khan, "Investigation and analysis of demand response approaches, bottlenecks, and future potential capabilities for IoT-enabled smart grid," 2024. doi: 10.1049/rpg2.13011.
[27] B. Sarkar, "Sustainable multi-biofuel production with stochastic lead time and optimum energy utilization under flexible manufacturing," *Comput. Ind. Eng.*, vol. 193, 2024, doi: 10.1016/j.cie.2024.110223.
[28] X. Li, "Urban biodiversity conservation: A framework for ecological network construction and priority areas identification considering habit differences within species," *J. Environ. Manage.*, vol. 365, 2024, doi: 10.1016/j.jenvman.2024.121512.
[29] D. Chen, "Spatial zoning to enhance ecosystem service co-benefits for sustainable land-use management in the Yangtze River economic Belt, China," *Ecol. Indic.*, vol. 159, 2024, doi: 10.1016/j.ecolind.2024.111753.
[30] J. Huang, "Green supply chain management: a renewable energy planning and dynamic inventory operations for perishable products," *Int. J. Prod. Res.*, vol. 62, no. 24, pp. 8924–8951, 2024, doi: 10.1080/00207543.2023.2220047.
[31] M. S. Habib, "Developing sustainable, resilient, and responsive biofuel production and distribution management system: A neutrosophic fuzzy optimization approach based on artificial intelligence and geographic information systems," *Appl. Energy*, vol. 372, 2024, doi: 10.1016/j.apenergy.2024.123683.
[32] H. Li, "Small Target Detection in Remote Sensing Images Based on Global Context Information," *Guangxue Xuebao Acta Opt. Sin.*, vol. 44, no. 24, 2024, doi: 10.3788/AOS240606.
[33] L. Wu, "User Side Resource Application and Key Technologies for Flexibility Demand of Renewable Energy Power System," *Dianwang Jishu Power Syst. Technol.*, vol. 48, no. 4, pp. 1435–1444, 2024, doi: 10.13335/j.1000-3673.pst.2023.0199.
[34] J. Zhu, "Dynamic collaborative optimization for disaster relief supply chains under information ambiguity," *Ann. Oper. Res.*, vol. 335, no. 3, pp. 1303–1329, 2024, doi: 10.1007/s10479-022-04758-5.
[35] P. Bao, "Efficient virtual power plant management strategy and Leontief-game pricing mechanism towards real-time economic dispatch support: A case study of large-scale 5G base stations," *Appl. Energy*, vol. 358, 2024, doi: 10.1016/j.apenergy.2024.122650.
[36] A. Kapoor, "Optimal Planning of Fast EV Charging Stations in a Coupled Transportation and Electrical Power Distribution Network," *IEEE Trans. Autom. Sci. Eng.*, vol. 21, no. 3, pp. 4261–4271, 2024, doi: 10.1109/TASE.2023.3293955.
[37] C. Dang, "IWRAM: A hybrid model for irrigation water demand forecasting to quantify the impacts of climate change," *Agric. Water Manag.*, vol. 291, 2024, doi: 10.1016/j.agwat.2023.108643.
[38] G. Alves-Ferreira, "'phyloraster': an R package to calculate measures of endemism and evolutionary diversity for rasters,'" *Ecography (Cop.).*, vol. 2024, no. 4, 2024, doi: 10.1111/ecog.06902.
[39] Q. Liu, "Optimal operation of coordinated multi-carrier energy hubs for integrated electricity and gas networks," *Energy*, vol. 288, 2024, doi: 10.1016/j.energy.2023.129800.
[40] W. Dong, "Enhanced integrated energy system planning through unified model coupling multiple energy and carbon emission flows," *Energy*, vol. 307, 2024, doi: 10.1016/j.energy.2024.132799.
[41] Y. Zhou, "Multi-period urban hydrogen refueling stations site selection and capacity planning with many-objective optimization for hydrogen supply chain," *Int. J. Hydrogen Energy*, vol. 79, pp. 1427–1441, 2024, doi: 10.1016/j.ijhydene.2024.07.067.
[42] L. Zhang, "PMP method with a cooperative optimization algorithm considering speed planning and energy management for fuel cell vehicles," *Int. J. Hydrogen Energy*, vol. 79, pp. 434–447, 2024, doi: 10.1016/j.ijhydene.2024.06.297.