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JOURNAL INDUSTRIAL SERVICESS

journal homepage: http://jurnal.untirta.ac.id/index.php/jiss

eISSN 2461-0631

Case study article

Determination of stock in inbound logistics based on optimal order quantity through Smart Application for Chicken Egg Stock (SAFCES)

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ARTICLE INFO

Article history:
Received 14 January 2025
Received in revised form 18 May 2025
Accepted 22 May 2025
Published online 24 May 2025

Keywords:
Optimal Order
Level Stock
SAFCES Application

Editor:
Anik Habyba

Publisher's note:
The publisher remains neutral concerning jurisdictional claims in published maps and institutional affiliations.

ABSTRACT

Ensuring a stable supply of chicken eggs to meet fluctuating market demand is essential for maintaining market stability and trader profitability. To address this challenge, the Smart Application for Chicken Egg Stock (SAFCES) was developed to optimize storage capacity for chicken eggs, extending beyond the traditional focus on determining order quantities. By employing a fuzzy logic approach, SAFCES accurately calculates the optimal order quantity and establishes minimum and maximum stock levels (Min-Max) to ensure consistent maintenance of ideal storage capacity. This innovative application enhances decision-making by providing traders with real-time insights into stock requirements, enabling them to adapt swiftly to demand variations. The implementation of SAFCES successfully supports traders in sustaining optimal stock levels, meeting both order and safety stock requirements, and keeping inventory within the desired thresholds. Furthermore, SAFCES promotes operational efficiency by reducing stockouts and overstocking, ultimately contributing to a more resilient supply chain for chicken eggs in dynamic market conditions.

1. Introduction

Many uncertainty factors influence supply chain management performance. These factors affect all dimensions of supply chain activities, making risks and vulnerabilities significant challenges for companies and organizations. Risk and uncertainty directly impact commodity yields, customer satisfaction, costs, and policies in supply chain activities [1]–[3]. To address these challenges, efficient inventory management is essential to enhance customer satisfaction, meet consumer demands, prevent product shortages, and maintain competitive product pricing [4]–[8].

Buffering techniques, such as safety stock, support manufacturing operational planning by managing demand and supply uncertainty to improve customer satisfaction [9]. Companies and business entities use safety stock to mitigate poor vendor performance, such as low-quality or delayed deliveries [10]. Safety stock is an effective strategy to prevent stock-outs and address variability in supply and demand [11]. Safety stock for finished products helps meet unexpected demand, while safety stock for raw materials protects against supply disruptions and production halts.

The Economic Order Quantity (EOQ) model is used to determine the optimal number of orders to suppliers, assuming stable demand, to reduce operational costs [12]–[14]. However, fluctuating prices, such as those for chicken eggs, complicate stakeholders' ability to determine optimal stock levels and order quantities, leading to high operational costs, shortages, or excess inventory. Therefore, developing a model to optimize chicken egg stock levels and supplier orders is necessary.

This research aims to develop an egg inventory model using the Min-Max method and fuzzy logic model, implemented as the Smart Application for Chicken Egg Stock (SAFCES).

The Min-Max Stock Level model is employed not only to determine the amount of stock in the warehouse but also to control stock within predefined minimum and maximum limits. Additionally, a fuzzy logic model is developed to optimize ordering from suppliers. Fuzzy logic facilitates decision-making by modeling

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http://dx.doi.org/10.62870/jiss.v11i1.30887

complex input parameters [15]–[18]. The input parameters for this fuzzy logic model include selling price, demand, supply, and available stock. The optimal order quantity derived from the fuzzy logic model serves as input for the Min-Max stock level method.

The Min-Max method was selected due to its compatibility with the fuzzy logic model, which effectively handles uncertainty in demand and supply. Unlike the EOQ model, which assumes static conditions, or Just-In-Time (JIT), which requires near-perfect coordination, the Min-Max method enables adaptive stock levels based on fuzzy outputs. This adaptability suits this research, given common demand fluctuations and imprecise data. Future studies could explore hybrid approaches, such as combining fuzzy logic with EOQ or JIT, to further optimize inventory management under varying conditions.

The development of the Smart Application for Chicken Egg Stock (SAFCES), a mobile application, facilitates inventory management by performing model-based calculations to verify stock levels. This application enables users to make informed decisions regarding available warehouse stock and the optimal number of orders to place with suppliers. SAFCES incorporates a machine learning model to enhance decision-making by processing experimental simulation data, optimizing algorithms for efficient data handling, selecting relevant features, and ensuring system reliability [19]–[24].

This research enhances chicken egg stock management for traders, ensuring consistent consumer demand fulfillment. For business owners, it provides a decision-making tool to determine optimal stock levels, maintaining stable egg inventory and enabling efficient business processes.

2. Material and method

2.1. Safety stock

This research focuses on market traders who sell to consumers and place orders with egg suppliers. The study employs the Min-Max method to calculate optimal stock levels, determining the ideal number of orders. This calculation integrates a fuzzy logic model to enhance the ordering process. The stock level calculations, according to [25], are shown in Eqs. (1)-(3),

$$SSt = \left(S_{max} - \bar{d}\right) \times lt \tag{1}$$

$$S_{min} = (\bar{d} \times lt) + SSt \tag{2}$$

$$S_{max} = 2 \times \left(\bar{d} \times lt\right) + SSt \tag{3}$$

where SSt denotes safety stock, S_{max} denotes maximum stock, S_{min} denotes minimum stock, $\bar{d}$ denotes average requirement, and lt denotes lead time.

2.2. Fuzzy logic

Fuzzy logic can be used to compute outputs for variables with imprecise values, where each variable is defined using linguistic terms [26]. The membership functions developed influence the defuzzification process, guided by an expanded fuzzy rule base [27], [28]. The optimal ordering of chicken eggs depends on variables with imprecise limits, including selling price, demand, supply, and stock availability. These variables are managed using fuzzy logic to calculate the optimal egg orders from suppliers. The steps for determining the optimal order using fuzzy logic are as follows.

2.1.1. Triangular membership function

Triangular membership functions are used to determine the degree of membership for variables based on their values within observed parameters [29]. Fuzzy inventory parameters (low, medium, high) for selling price, demand, supply, and stock were established through statistical analysis of daily market data (e.g., mean and standard deviation) and consultations with egg traders to ensure practical applicability. For example, demand ranges were defined as low (0–30 kg), medium (30–70 kg), and high (> 70 kg), derived from historical data distributions and refined through iterative fuzzy logic model testing. This approach ensures accurate thresholds aligned with the dynamics of the chicken egg market. The triangular membership function is mathematically defined as $\mu\_F(a, b, c)\colon \mathbb{R} \rightarrow [0,1]$ [30].

2.1.2. Trapezoidal membership function

The trapezoidal membership function defines the degree of membership for each parameter, assigning a maximum value of 1 to a range of values within the parameter [31]. The trapezoidal membership function is mathematically expressed as $\mu\_F(a, b, c, d)\colon \mathbb{R} \rightarrow [0,1]$ [32], [33].

2.1.3. Fuzzy rule base

Fuzzy rules define possible conditions based on the parameters of variables used to develop the membership set model. These rules establish constraints for determining the fuzzy operator, enabling the identification of the moment and region during the defuzzification process. The fuzzy rule model can be expressed as follows: If x_1 is A_{i1} and … and x_n is A_{in}, then Class C_i with CF_i, where $i = 1, \ldots, n$, and the set $X = \{x_1, x_2, \ldots, x_n\}$ [34].

2.1.4. Deffuzyfication

The defuzzification process converts the fuzzy membership set into a crisp output value. The Center of Area (COA) method is used, which calculates the output by evaluating the moment and area in the defuzzification process. The formulation of the COA method, based on [35], is expressed in Eq. (4).

$$Xcoa = \frac{\int_{x=0}^{n} \mu A(x) x \, dx}{\int_{x=0}^{n} \mu A(x) \, dx} \tag{4}$$

Table 1
Optimal order fuzzy variable membership set

No	Variable	Parameter		
		Low	Medium	High
1	Selling price (thousand rupiahs)	18; 18; 19; 21	20; 22; 24	23; 25; 26; 26
2	Demand (kg)	35; 35; 40; 50	45; 52,5 ; 60	55; 65; 80; 80
3	Supply (kg)	0; 0; 15; 60	45; 75; 150	90; 120; 150; 150
4	Stock (kg)	0; 0; 15; 45	30; 75; 120	100; 150; 225; 225
5	Optimal order (kg)	20; 50; 80	60; 110; 160	120; 170; 225

2.3. *Smart Application for Chicken Egg Stock (SAFCES)*

The SAFCES application, developed in Python using the scikit-fuzzy library, implements fuzzy logic and integrates with a Flask web interface for real-time data processing. Its fuzzy logic model, combining triangular and trapezoidal membership functions with 243 IF-THEN rules, is stored in a database and uses the Centre of Area defuzzification method to compute optimal stock sequences. The Min-Max model serves as a stock calculation module. Initially validated in MATLAB, the fuzzy logic model was adapted into SAFCES to provide automated stock management for egg traders.

Model verification involved comparing SAFCES outputs—such as an optimal order of 121 kg and stock levels (safety stock: 71 kg, minimum: 121 kg, maximum: 171 kg)—with manual MATLAB calculations to ensure numerical consistency. The process included real-time market data processing in SAFCES and scenario simulations to validate recommendations against actual conditions. Triangular membership functions were chosen for selling price, supply, and stock due to their centered, stable distributions, as confirmed by histogram analysis of daily market data. For demand, a combination of triangular and trapezoidal functions was selected to capture its high variability and stable plateaus, with trapezoidal functions better representing flat regions in the data. This choice aligns with the dynamic characteristics of chicken egg market demand.

3. Results and discussion

This research focuses on the Kemang Perumda Market and Tohaga Market in Bogor Regency. Egg orders at Kemang Market are managed to ensure consistent supply availability, but current stock management fluctuates, leading to inconsistent stock levels. The variables influencing optimal egg ordering decisions at Tohaga Market are selling price, demand (kg), supply (kg), and total stock (kg). These variables have imprecise ranges, necessitating a fuzzy logic approach to determine optimal egg orders and maintain stable stock levels. The optimal order model will be implemented in the Smart Application for Egg Stock (SAFCES). The membership functions for the fuzzy variables are presented in Table 1.

Based on the fuzzy membership set, the membership set model is developed to determine the moment and area according to the fuzzy rules applied.

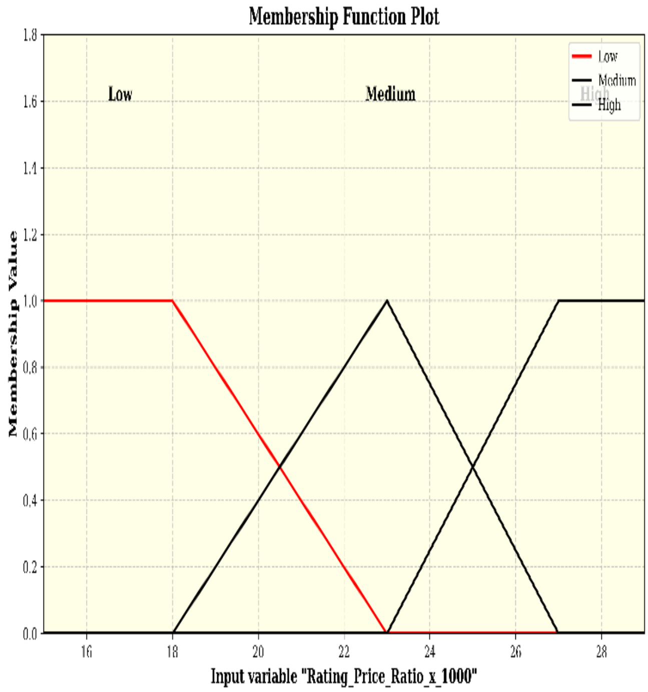

Fig. 1. Model of membership set selling price of chicken eggs

3.1. *Membership association*

The input variable used to determine the optimal order is the selling price of chicken eggs (in kilograms). This variable has three parameters: low, medium, and high, with trapezoidal and triangular membership set graphs. The membership set model for the selling price of chicken eggs is shown in Fig. 1. Based on the optimal membership set, the degree of membership can be determined. The current price of chicken eggs is IDR 24,000, resulting in a membership degree value of μ_high price [24,000] = 0.5.

The next input variable used to determine the optimal order is the market demand for chicken eggs. Demand management is developed using a fuzzy approach, where this variable has three parameter limits: low, medium, and high, with a combination of triangular and trapezoidal membership sets. These membership sets are derived from the limitations of demand parameters in the market. The membership set model for chicken egg demand can be seen in Fig. 2. Based on the membership association, the selling price of chicken eggs is determined by the degree of membership, which reflects real market conditions. The current demand for chicken eggs is 50 kg, resulting in a membership degree value of μ_middle demand [50] = 0.67.

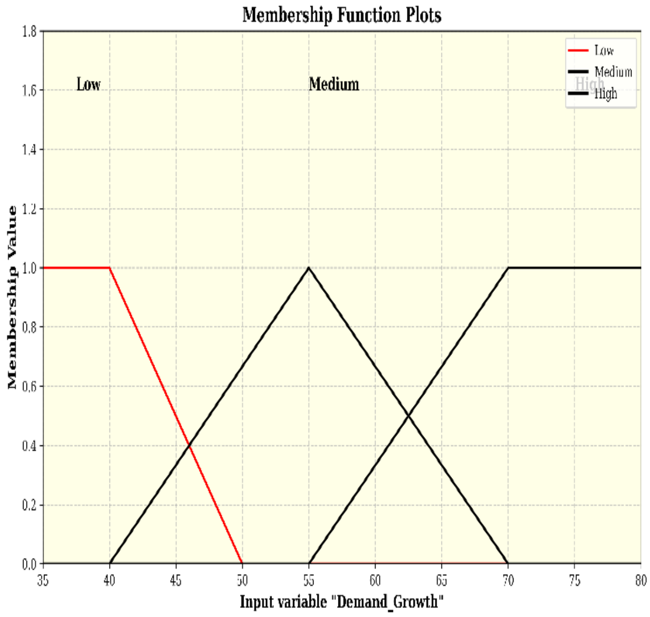

Fig. 2. Model of membership set demand of chicken eggs

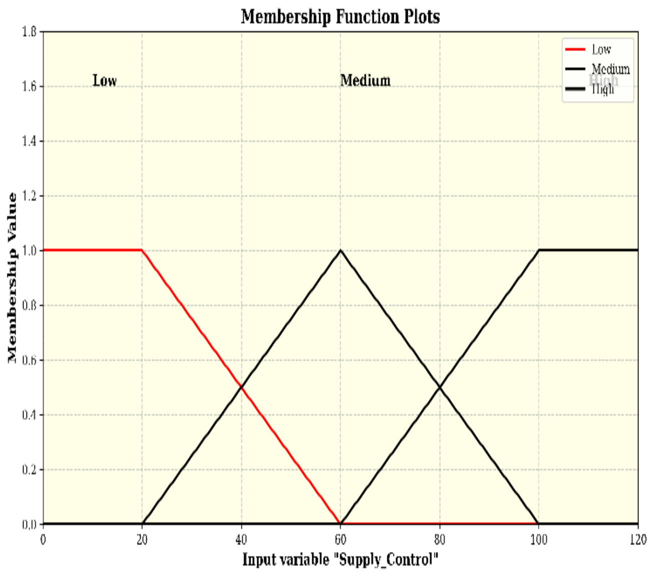

Fig. 3. Model of membership set suppply of chicken eggs

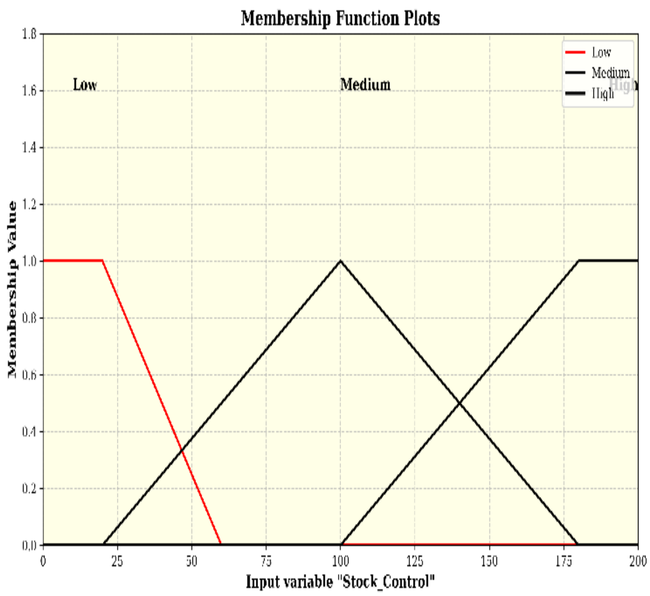

Fig. 4. Model of membership set suppply of chicken eggs

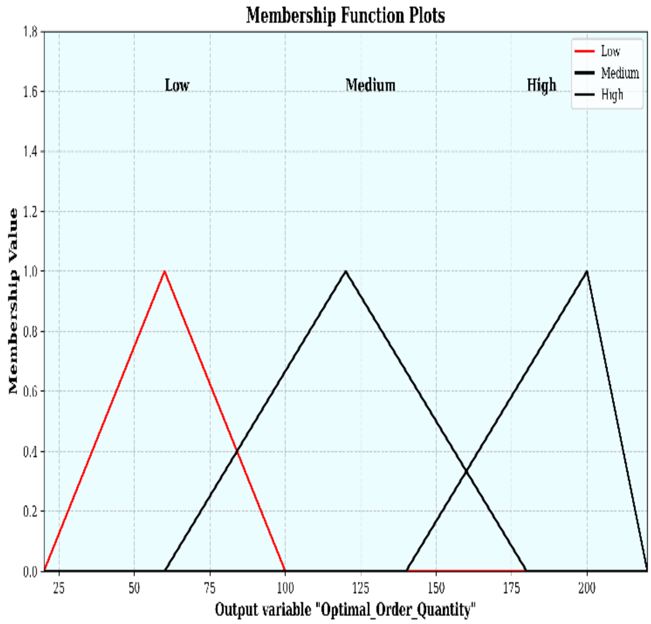

Fig. 5. Model of membership set order quantity of chicken eggs

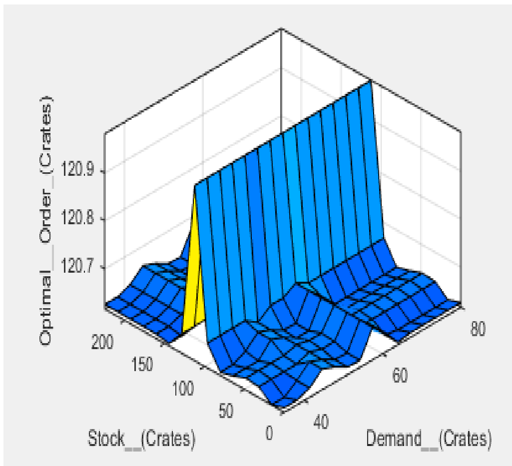

Fig. 6. Surface optimal order of chicken eggs

The next variable used to determine optimal orders for chicken eggs from suppliers is the egg supply to the market (in kg). The model for the chicken egg supply is shown in Fig. 3. The parameter value used to determine the degree of membership for the supply of chicken eggs in the market is 150 kg, representing the highest supply of chicken eggs. The membership degree for chicken egg supply is µ_high stock [150] = 1.

The next variable used to determine the optimal order is the stock condition of chicken eggs in the market. This stock condition must be considered to ensure that the market stock level is well maintained. The model for the membership set of chicken egg stock conditions in the market is shown in Fig. 4.

The parameter value for stock conditions in the market, used to determine the optimal order, is 25 kg. Constraints define the degree of stock membership, with µ_*low* stock [25] = 0.67. Based on the membership degree values of the four input variables—selling price, demand, supply, and stock of chicken eggs in the market—the fuzzy operator value used in the defuzzification process for determining optimal orders of chicken eggs can be calculated. The model for the optimal order membership set is shown in Fig. 5.

Table 2
Comparison of stock conditions and stock level

No	Conditions	Value
1	Available Stock (kg)	25
2	Safety Stock (kg)	71
3	Min Stock (kg)	121
4	Max Stock (kg)	171
5	Status	Not Safe

3.2. Fuzzy rule base

Based on the membership set model, which consists of input variables—namely selling price, demand (kg), supply (kg), and stock amount (kg)—and an output variable, namely optimal order (kg), there are 243 possible fuzzy rules determined by the conditions of these parameters in the market. The fuzzy rules are constructed using the "AND" operator in the "IF-THEN" format.

Based on the values of the input variable parameters, the fuzzy operator value (α) is obtained by taking the minimum membership degree among the input variables for the optimal order. The characteristics of the optimal order membership set, the input variable model, and the resulting fuzzy rules can be visualized using the surface graph in Fig. 6.

3.3. Optimal order defuzzyfication

The defuzzification process uses the Center of Area (COA) method by comparing the moment value and the area of the optimal order fuzzy membership set. Based on the input variables, the resulting fuzzy operator has a value of 0.5. The optimal order fuzzy membership set derived from this fuzzy operator are shown in Eqs. (5)-(14). Based on the membership set that occurs, the moment value for the optimal order defuzzification process for chicken eggs can be determined. Moments generated based on the optimal order membership set for chicken eggs in the market are as shown in Eqs. (15)-(23).

$$Fx(a,b,c,d) = 0 \quad x \leq 20 \tag{5}$$

$$Fx(a,b,c,d) = \frac{x-20}{30} \; 20 \leq x \leq 35 \tag{6}$$

$$Fx(a,b,c,d) = 0{,}5 \;\; 35 \leq x \leq 65 \tag{7}$$

$$Fx(a,b,c,d) = \frac{80-x}{30} \; 65 \leq x \leq 80 \tag{8}$$

$$Fx(a,b,c,d) = \frac{x-60}{50} \; 60 \leq x \leq 85 \tag{9}$$

$$Fx(a,b,c,d) = 0{,}5 \;\; 85 \leq x \leq 135 \tag{10}$$

$$Fx(a,b,c,d) = \frac{160-x}{50} \; 135 \leq x \leq 160 \tag{11}$$

$$Fx(a,b,c,d) = \frac{x-120}{50} \; 120 \leq x \leq 145 \tag{12}$$

$$Fx(a,b,c,d) = 0{,}5 \;\; 145 \leq x \leq 197.5 \tag{13}$$

$$Fx(a,b,c,d) = \frac{225-x}{55} \; 197{,}5 \leq x \leq 225 \tag{14}$$

$$Moment\ 1: \int_{20}^{35} 0{,}033\ x2 - 0{,}67\ x\ dx \tag{15}$$

$$Moment\ 2: \int_{35}^{65} 0{,}5\ x\ dx \tag{16}$$

$$Moment\ 3: \int_{65}^{80} 2{,}67\ x - 0{,}033\ x2\ dx \tag{17}$$

$$Moment\ 4: \int_{60}^{85} 0{,}02\ x2 - 1{,}2x\ dx \tag{18}$$

$$Moment\ 5: \int_{85}^{135} 0{,}5x\ dx \tag{19}$$

$$Moment\ 6: \int_{135}^{160} 3{,}2\ x - 0{,}02\ x2\ dx \tag{20}$$

$$Moment\ 7: \int_{120}^{145} 0{,}02\ x2 - 2{,}4\ x\ dx \tag{21}$$

$$Moment\ 8: \int_{145}^{197{,}5} 0{,}5\ x\ dx \tag{22}$$

$$Moment\ 9: \int_{197.5}^{225} 4{,}1x - 0{,}02\ x2\ dx \tag{23}$$

Based on actual conditions, there are nine moments in the optimal membership order set, with a total moment value of 12,024.37. This total moment is then compared with the total area in the optimal order defuzzification process. According to the condition of the optimal order membership set, the total area is 99.375. Using the moment and area values from the defuzzification process, the optimal order for chicken eggs is calculated to be 121 kg. Verification of the optimal order calculation model was conducted using the MATLAB.

The result of the optimal order quantity calculation using the fuzzy logic model is 121 kg. Safety stock is calculated daily to assess the traders' daily needs. Since chicken egg traders replenish their inventory daily, the lead time is assumed to be one day. In the safety stock calculation, the optimal order quantity is assumed to represent the maximum stock that must be provided, while the average demand is assumed to be the number of requests received on that day.

The calculation of stock levels based on fuzzy rules for optimal order quantity has been verified using the SAFCES software. This application records four real-time input parameters daily: selling price, demand, supply, and available stock. Using these daily recaps, the fuzzy logic model is further validated through the optimal order interface in SAFCES.

Future research could consider integrating storage time as a fifth parameter. For instance, fuzzy logic could be used to define rules such as, "If storage time is high and demand is low, then reduce stock orders to avoid spoilage." Implementing this would require collecting additional data on storage duration and conditions, which could be made easier with digital inventory tracking systems.

Based on the verified stock level calculation method and the SAFCES interface, the ideal inventory capacity for market traders includes a safety stock of 71 kg, a minimum inventory of 121 kg, and a maximum inventory of 171 kg. These figures were derived from simulation tests comparing actual stock conditions with the proposed stock level model. The simulation results are presented in Table 2. Based on the simulation comparison above, the current available stock is only 25 kg, indicating a shortage. To address this, traders need to place an order for 167 kg of chicken eggs from suppliers. This consists of 121 kg as the optimal order quantity and an additional 46 kg to restore the safety stock. This ensures that consumer demand can be met and inventory levels remain stable.

In the fuzzy logic model used in this study, the selling price was one of the four input parameters—alongside demand, supply, and available stock—used to determine the optimal order quantity. Although the specific price value was not explicitly mentioned in the simulation comparison for the sake of brevity, the model incorporated the average selling price of chicken eggs during the study period, which was approximately IDR 28,000 per kg (based on market data collected through daily recaps). This price input was essential for evaluating the economic feasibility of the recommended order quantities.

For example, ordering the optimal quantity of 121 kg would cost approximately IDR 3,388,000 (121 kg × IDR 28,000/kg), while the additional 46 kg required to replenish the safety stock would cost IDR 1,288,000 (46 kg × IDR 28,000/kg), bringing the total cost of the 167 kg order to IDR 4,676,000.

The selling price also influenced the Min-Max stock level method by impacting the maximum inventory threshold. Higher prices may encourage lower stock levels to minimize holding costs, whereas lower prices may justify higher inventory levels to ensure product availability. In this case, the price of IDR 28,000 per kg was relatively stable throughout the simulation period, allowing the model to focus primarily on quantity adjustments rather than price fluctuations.

This study determined an optimal order quantity of 121 kg for chicken eggs, with corresponding stock levels—71 kg of safety stock, a minimum of 121 kg, and a maximum of 171 kg—using a fuzzy logic model integrated with the Min-Max method, as verified through the SAFCES application. These findings align with the work of [29], who also applied fuzzy logic to optimize egg ordering and achieved accurate stock predictions under variable market conditions.

However, unlike [26], who focused on dynamic decision-making in broader supply chains using fuzzy logic, the present study specifically addresses the management of perishable goods—namely chicken eggs—through daily market recaps. This approach offers a more tailored solution for short-term inventory control. Compared to traditional Economic Order Quantity (EOQ) models, which assume static demand [8], the fuzzy logic approach employed here more effectively manages demand uncertainty. This is evidenced by its ability to address the 25 kg stock deficit identified in Table 2, reducing the risk of shortages.

Overall, this study contributes to the field of adaptive inventory management for perishable goods and suggests future research could explore supplier performance evaluation, as outlined in the conclusions, to further enhance supply chain resilience.

4. Conclusions

Development of methods in inventory control using the stock level with reference to the optimal number of orders by using a fuzzy logic model. The model is verified by developing SAFCES application that can provide information in decision making for the market party in managing the available stock. Based on the interface for the optimal number of orders and the ideal capacity of SAFCES is 167 kg. This model provides practical guidance for egg agents to as a decision support in determining the availability of chicken egg stock. Further research can develop an evaluation model on the performance of chicken egg suppliers to obtain alternative strategies for chicken egg supply.

Declaration statement

Agung Prayudha Hidayat: Conceptualization, Methodology; Writing Original Draft. **Sesar Husen Santosa**: Formal Analysis, Formulation. **Ridwan Siskandar**: Collecting Data, Supervised. **Derry Dardanella**: Review and Investigation. **Putro Ferro Ferdinant**: Supervised and Validation.

Acknowledgement

The author would like to thank the IPB University Vocational School and the Blessed Egg Agent who helped to complete this research.

Disclosure statement

The author declares that this manuscript is free from conflict of interest and is processed by applicable journal provisions and policies to avoid deviations from publication ethics in various forms. The authors declare no conflicts of interest. The authors report there are no competing interests to declare.

Funding statement

The authors received no funding for this research.

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article or its supplementary materials.

AI Usage Statement

The authors confirm that no generative AI or AI-assisted tools were used in the creation or writing of this manuscript. All content has been entirely produced, reviewed, and edited by the authors without the assistance of AI technologies.

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