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Bullwhip Effect Identification, ARIMA/SARIMA Demand Forecasting, and EOQ-Based Inventory Control at a Chicken Egg Distributor: A Case Study of Distributor X

***Olga Monica**
Universitas Indonesia, Indonesia

Ratih Dyah K
Universitas Indonesia, Indonesia

***Corresponding author:**
Olga Monica, Universitas Indonesia, Indonesia. ✉olga.monica@office.ui.ac.id

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Abstract

Background: Effective inventory management is crucial for maintaining supply stability and avoiding imbalances between demand and product availability. In practice, poorly managed demand fluctuations can trigger the bullwhip effect, leading to supply chain inefficiencies.
Objective: This study aims to analyze the bullwhip effect phenomenon in chicken egg inventory at Distributor X, identify the most accurate forecasting model, and formulate appropriate inventory policies.
Methods: This study employed a quantitative descriptive case-study design using three years (2023–2025) of historical operational data. The analyses included bullwhip effect measurement, ARIMA/SARIMA demand forecasting, and inventory optimization using EOQ, safety stock, reorder point (ROP), and total inventory cost (TIC). Supporting interviews were conducted to interpret the company's operational practices.
Results: The bullwhip effect values of 1.4 for regular eggs and 1.3 for omega eggs exceed the threshold value of 1.12, confirming demand amplification along the supply chain. ARIMA (0,0,1) provided the best fit for regular eggs (MAPE: 4.2%), while SARIMA (1,0,1)(0,1,1)[12] provided the best fit for omega eggs (MAPE: 6.8%). EOQ analysis yielded optimal order quantities of 245 kg and 265 kg, respectively, with safety stocks of 17 kg and 52 kg, and reorder points of 543 kg and 669 kg. Total inventory costs are projected to decrease by approximately 5–7% during 2026–2028 compared to the 2023–2025 period.
Conclusion: The integration of ARIMA/SARIMA-based forecasting and EOQ inventory control demonstrates measurable improvements in demand prediction accuracy and inventory cost efficiency, reducing total inventory costs by 5–7% and providing a systematic framework for mitigating the bullwhip effect at Distributor X.

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INTRODUCTION

Supply chain management (SCM) is a crucial factor in improving the efficiency of product, information, and financial flows in the food industry, which is characterized by perishable products (Haji et al., 2020; Imen & Abdelkarim, 2024; Mirabelli & Solina, 2022). Market developments, changes in consumer consumption patterns, and increasing complexity of distribution networks require companies to build responsive and integrated supply chains. In the food industry, supply chain effectiveness is determined not only by the ability to meet customer demand but also by the ability to manage demand uncertainty, distribution, and inventory simultaneously. Therefore, companies need to develop supply chain strategies that enhance information visibility, improve coordination among supply chain actors, and reduce operational inefficiencies.

Chicken eggs are a strategic food commodity with a high consumption rate in Indonesia. However, based on the Outlook for Livestock Commodities for Laying Hens from the Ministry of Agriculture of the Republic of Indonesia (2023), Indonesia is projected to experience an egg production surplus in the 2025–2027 period. This condition indicates that the main challenge in the poultry sector lies not only in increasing production but also in the supply chain's ability to distribute products effectively from producers to end consumers. If the distribution flow is not managed optimally, the production surplus has the potential to cause inventory buildup, increased logistics costs, decreased product quality, and an imbalance between supply and market demand.

According to data from the Central Statistics Agency (BPS, 2024), national egg production reached approximately 5.8 million tons in 2023, while domestic consumption grew at a slower rate of 3–4% annually. This surplus creates significant distribution challenges, particularly for medium-scale distributors who lack sophisticated inventory management systems. A survey by the Indonesian Poultry Farmers Association (GPPU, 2023) revealed that nearly 40% of egg distributors in Java still rely on manual ordering without demand forecasting tools, resulting in an estimated 8–12% product loss due to spoilage and inefficient stock management.

One of the main problems in supply chain management is the emergence of the bullwhip effect, a condition in which demand variation amplifies at each level of the supply chain compared to actual consumer demand. This phenomenon causes information distortion, leading to inefficient ordering, production, and distribution decisions. According to Heizer (2020), the bullwhip effect is generally triggered by demand forecasting errors, large batch ordering policies, price fluctuations, limited supply, and poor-quality information exchange among supply chain members. The impact is not only increased inventory costs but also higher transportation, distribution, and overall coordination costs across the supply chain.

In chicken egg distribution companies, the bullwhip effect becomes even more critical due to the perishable nature and limited shelf life of the product. When overstock occurs, companies face risks of product quality degradation and increased storage costs. Conversely, understock conditions can lead to delivery delays and decreased customer service levels. Therefore, supply chain management requires a data-driven decision-making system to balance market demand with distribution capabilities.

One widely used approach to improve supply chain performance is the integration of demand forecasting and inventory control processes. In the concept of Collaborative Planning, Forecasting, and Replenishment (CPFR), demand information is used as a basis for aligning planning, procurement, and distribution activities along the supply chain. This approach allows companies to reduce demand uncertainty and improve coordination among supply chain actors. According to Zellner et al. (2021), forecasting is a crucial component in SCM as it serves as the basis for decision-making regarding production, distribution, and capacity planning.

Time series forecasting methods such as the Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) have been widely used to predict demand in various industrial sectors (Kruba et al., 2025). ARIMA is effective for data with non-seasonal patterns, while SARIMA accommodates seasonal patterns that often appear in food product demand (Hyndman & Athanasopoulos, 2018). In the supply chain context, accurate forecasting can reduce demand uncertainty, making procurement and distribution decisions more effective. Furthermore, forecasting results can be integrated with inventory control policies such as Economic Order Quantity (EOQ), safety stock, and Reorder Point (ROP) to support smooth product flow in the supply chain.

Previous research has discussed forecasting and inventory control separately, but integration of bullwhip effect analysis, forecasting, and inventory policy within a single supply chain management framework remains relatively limited. Klaharn (2024) showed that SARIMA provides high accuracy in the poultry industry, which exhibits seasonal patterns, while Fanoodi (2019) found that ARIMA is more effective for fluctuating demand. However, most research still focuses on individual aspects of forecasting or inventory and has not examined how forecasting results can be used to reduce the bullwhip effect and improve overall supply chain efficiency. Therefore, this study contributes by integrating bullwhip effect measurement, ARIMA/SARIMA forecasting, and inventory policies in the context of chicken egg distribution.

The novelty of this research lies in the development of an integrated analytical framework that combines bullwhip effect measurement, ARIMA/SARIMA demand forecasting, and EOQ-based inventory control within a single study, an approach that has not been comprehensively applied in the chicken egg distribution sector. In addition, this study adopts a product-specific forecasting strategy by selecting ARIMA for non-seasonal demand patterns and SARIMA for seasonal demand patterns, allowing each model to better represent the characteristics of different egg products. Furthermore, the research establishes a direct linkage between forecasting outputs and inventory control parameters, including Economic Order Quantity (EOQ), safety stock, and Reorder Point (ROP), resulting in a practical decision-support framework that improves inventory planning and supply chain efficiency for perishable food distributors, particularly in developing countries.

Specifically, Klaharn et al. (2024) focused exclusively on forecasting accuracy in poultry production without linking results to inventory decisions, applied ARIMA-based forecasting in manufacturing without considering perishable product constraints or the bullwhip effect. Suharjito (2024) measured the bullwhip effect in salt distribution but did not integrate forecasting models with inventory optimization. A critical gap exists in that no prior study has simultaneously examined the bullwhip effect, applied both ARIMA and SARIMA for product-specific forecasting, and formulated integrated inventory policies (EOQ, safety stock, and ROP) within the perishable food distribution sector. Furthermore, previous studies have predominantly been conducted in manufacturing or non-perishable commodity contexts Chen (2012), leaving the unique challenges of perishable food supply chains (such as limited shelf life, quality degradation risk, and seasonal demand fluctuations) largely unaddressed within an integrated analytical framework.

Distributor X, as a chicken egg distributor, faces challenges in maintaining the balance between supply and demand due to demand fluctuations and decision-making that is still intuitive. This condition has the potential to cause information distortion and increase the risk of the bullwhip effect in the company's supply chain. Based on these problems, this study aims to analyze the supply chain at Distributor X by identifying the bullwhip effect and determining the most accurate forecasting model using ARIMA and SARIMA methods, as well as formulating inventory control policies that support improved supply chain efficiency. Thus, this research focuses not only on inventory optimization but also on overall supply chain performance improvement by reducing demand variability, increasing information accuracy, and strengthening distribution coordination.

Academically, this research enriches the literature on the integration of forecasting and inventory control from a supply chain management perspective for perishable products. Practically, the results are expected to serve as a basis for companies to design more responsive, efficient, and sustainable supply chain strategies, particularly in facing the risk of production surplus and demand uncertainty in the chicken egg distribution industry.

From a theoretical perspective, this research contributes to the supply chain management literature by demonstrating the interconnection between demand variability (bullwhip effect), forecasting accuracy, and inventory efficiency in perishable food distribution. The findings extend the applicability of ARIMA/SARIMA models beyond manufacturing and non-perishable goods to the perishable food sector, validating their effectiveness under conditions of limited shelf life and seasonal demand fluctuations. From a practical standpoint, the integrated framework developed in this study provides actionable guidelines for chicken egg distributors to transition from intuition-based to data-driven inventory management, potentially reducing inventory costs, minimizing product waste, and improving customer service levels. The findings are also applicable to other perishable food distribution businesses facing similar supply chain challenges in developing economies.

METHOD

This study, "Bullwhip Effect Identification, ARIMA/SARIMA Demand Forecasting, and EOQ-Based Inventory Control at a Chicken Egg Distributor: A Case Study of Distributor X", employed a quantitative approach using a descriptive case study design to systematically analyze inventory management and supply chain performance at Distributor X, a medium-scale chicken egg distributor. The descriptive case study design was selected to provide an in-depth analysis of inventory-related problems, particularly the imbalance between customer demand and stock availability, which contributes to the bullwhip effect. Quantitative analysis was conducted using bullwhip effect measurement, ARIMA/SARIMA demand forecasting, Economic Order Quantity (EOQ), safety stock, reorder point (ROP), and total inventory cost (TIC), while interviews and field observations were used only to support the interpretation of operational conditions and inventory management practices.

The research was conducted at Distributor X in Semarang City using historical operational data collected during the 2023–2025 period. The study focused on supply chain conditions, product distribution patterns, inventory control, reordering processes, and demand patterns for regular and omega chicken eggs. Furthermore, it examined the relationship between demand forecasting and inventory management effectiveness in maintaining distribution stability. The integration of historical operational data with supporting qualitative information provided a comprehensive understanding of the operational factors influencing demand variability and inventory performance.

This research focuses on historical sales and ordering data for chicken eggs from January 2023 to December 2025 originating from the company's main customers. The data used include demand data, sales data, inventory levels, distribution lead time, order frequency, and costs related to procurement, storage, and product distribution activities. These data are used to analyze the bullwhip effect phenomenon, build demand forecasting models using ARIMA/SARIMA methods, and formulate optimal inventory control policies. In time-series analysis, the data are not required to be normally distributed; instead, the emphasis is placed on meeting the assumption of stationarity. Normality testing is conducted on model residuals at the diagnostic stage to ensure that the resulting model meets the required statistical criteria.

This research also involved the company's internal parties as the main source of information, especially the production and distribution divisions that understand the overall supply chain operational process. Data collection techniques were carried out through observation, interviews, and documentation. Direct observation of the company's operational activities was conducted to understand the distribution flow, stock recording system, and procurement process. In-depth interviews with company representatives were conducted to obtain information regarding inventory policies, decision-making processes, and constraints faced in supply chain management. Meanwhile, documentation was used to obtain supporting data in the form of sales reports, order data, distribution records, and company operational archives. The research instruments used were interview guides, observation sheets, and company documents related to distribution and inventory control activities. The use of multiple data collection techniques aimed to obtain more comprehensive data and enhance the validity of the research findings.

A total of three key informants were selected using a purposive sampling technique based on their direct involvement in the company's supply chain operations: (1) the owner/manager of Distributor X, who oversees overall business decisions, including procurement and pricing; (2) the warehouse supervisor, responsible for daily stock recording and inventory monitoring; and (3) the distribution coordinator, who manages order fulfillment and delivery scheduling. Data validation was conducted through triangulation of sources, comparing information obtained from interviews with observational data and company documentation to ensure consistency and reliability of the findings.

This research is designed to produce relevant solutions to inventory management problems at Distributor X by analyzing current supply chain conditions. The research strategy was carried out through several systematic analytical stages, namely bullwhip effect analysis, demand forecasting, and determination of inventory policies.

The procedure for selecting the best forecasting model followed the Box–Jenkins methodology (Hyndman & Athanasopoulos, 2018). First, data stationarity was tested using the Augmented Dickey–Fuller (ADF) test. Second, candidate models were identified through visual inspection of autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. Third, multiple candidate ARIMA/SARIMA models were estimated, and the best model was selected based on the lowest Akaike Information Criterion (AIC) and Bayesian Information

Criterion (BIC) values. Fourth, diagnostic checking was performed on the selected model, including the Ljung–Box test for residual autocorrelation and the Shapiro–Wilk test for residual normality. Model accuracy was evaluated using mean absolute percentage error (MAPE), mean squared error (MSE), and mean absolute deviation (MAD).

1. Bullwhip effect analysis aims to measure the level of demand distortion in the supply chain. This analysis was performed by comparing demand variability and order variability using the coefficient of variation. The formula used is as follows:

$$\omega = \frac{C_{out}}{C_{in}} \tag{1}$$

In which:

$$C_{in} = \frac{\sigma(D_{in})}{\mu(D_{in})} \tag{2}$$

$$C_{out} = \frac{\sigma(D_{out})}{\mu(D_{out})} \tag{3}$$

Information:

ω	: Bullwhip Effect
Cin	: Demand variability
Cout	: Sales variability
σ	: Standard deviation
μ	: Mean
Din	: Total Demand
Dout	: Total Sales
L	: Lead time
P	: Periode (in months)

2. Demand forecasting using the Autoregressive Integrated Moving Average (ARIMA) method. This method is used to predict future demand based on historical time series data. Generally, the ARIMA model is expressed as ARIMA (p,d,q) in the form (Hyndman & Athanasopoulos, 2018):

$$(1\text{-}\emptyset_1 B - \cdots - \emptyset_p B^p(1-B)^d y_t = c + (1 + \theta_1 B + \cdots + \theta_Q B^q)e_t \tag{4}$$

Information:

y_t	: Variable value at time t
$y_{t-1}, y_{t-2}, \ldots, y_{t-p}$	: Variable value at previous periods (lags)
c	: Constant (intercept)
$\emptyset_1, \emptyset_2, \ldots, \emptyset_p$	: coefficients of autoregressive (AR)
$\theta_1, \theta_2, \ldots, \theta_p,$	: coefficients of moving average (MA)
e_t	: Error/ residual at time t
$e_{t-1}, e_{t-2}, \ldots, e_{t-q}$	: Error at previous periods

3. Determination of inventory policies was carried out using several inventory control models, namely Economic Order Quantity (EOQ), Safety Stock, Reorder Point (ROP), and Total Inventory Cost (TIC). EOQ according to Heizer (2020) is described as follows:

$$\text{EOQ:} \sqrt{\frac{2DS}{H}} \tag{5}$$

Information:

EOQ	: Optimal order quantity
S	: Ordering cost
D	: Annual demand (unit/year)
H	: Holding cost per unit per year.

The formula for calculating safety stock according to Heizer (2020) is described as follows:

$SS = Z \times \sigma d \times \sqrt{L}$ (6)

Information:
SS : Safety stock
Z : Service level
σ : Standard deviation of *demand*
L : Lead time

The formula for calculating *reorder point* according to Heizer (2020) is described as follows:

ROP = d x L + SS (7)

Information:
ROP: Reorder point.
D: Demand rate per unit time.
L: Lead time.

The formula for calculating TIC according to Heizer (2020) is described as follows:

$TIC = \frac{D}{Q} S + \frac{Q}{2} H$ (8)

Information:
D: Annual demand (unit/year)
Q: Order quantity per order (unit)
S: Ordering cost per order
H: Holding cost per unit per year

RESULTS AND DISCUSSION

Results

Bullwhip Effect Analysis

In this study, the bullwhip effect is measured using the ω parameter as an indicator to assess the level of demand amplification in the supply chain. This parameter is calculated considering lead time and observation period to reflect the relationship between supply and demand variability. The parameters used in this study are as follows:

Lead Time (L): 2 days
Observation period: 36 months / 1,080 days
The *Bullwhip Effect* parameter (ω) is calculated using the formula:

$1 + \frac{2 \times 2}{36} + \frac{2 \times 2^2}{36^2} = 1.12$ (9)

Table 1. *Bullwhip Effect* Values at Distributor X

Product	**Supply**			**Demand**			**Value**	**Parameter**	**Description**
	σ	μ	CV Supply	σ	μ	CV Demand	**ω**	**ω**	
Regular Chicken Egg	863,09	7835,09	1,4	1,12	Amplification of demand occurs	0,08	1,4	1,12	Amplification of demand occurs
Omega Chicken Egg	1024,04	9800.,2	1,3	1,12	Amplification of demand occurs	0,08	1,3	1,12	Amplification of demand

occurs

This parameter value is used as a threshold to determine whether a bullwhip effect occurs. If the actual ω value is greater than the parameter (ω > 1.12), it indicates demand amplification in the supply chain.

Demand Forecasting

After model testing, the best models for each product were obtained. The mathematical equations for the selected models can be stated as follows:

a. Regular Chicken Egg

Based on parameter estimation and model testing results, the best model for the regular chicken egg product is ARIMA (0,0,1), which falls into the category of Moving Average order 1 (MA(1)). This model shows that the forecast value at time t is influenced by a constant of 7882.9 and the error from the previous period with a coefficient of 0.381. Mathematically, the model equation can be written as follows:

$$\widehat{Z_t} = 7882.9 - 0.381\alpha_{t-1} \ (10)$$

Where:
$\widehat{Z_t}$: Forecast value at time t
7882.9 : Constant
0.381 : Moving average coefficient of order 1
α_{t-1} : Error in the previous period

The ARIMA (0,0,1) model indicates that the forecast value is not influenced by historical values but by the error in the previous period. This suggests that demand fluctuations are more influenced by short-term shocks.

b. Omega Chicken Egg

For the omega chicken egg product, the best model obtained is SARIMA (1,0,1)(0,1,1)[12], which indicates a seasonal component with a period of 12 months. Mathematically, the equation for this model is as follows:

$$(1 - 0.728\mathrm{B})(1 - B^{12})y_t = -5.15 + (1 + 0.998B)(1 + 0.726B^{12})e_t \ \ (11)$$

Where:
$\Phi_P(B^m)$: 1
$\Theta_Q(B^m)$: $(1 + 0.726B^{12})$
$\phi_p(B)$: $(1 - 0.728\mathrm{B})$
$\theta_q(B)$: $(1 + 0.998B)$
c=−5.15
$(1 - B)^d$: 1
$(1 - B^m)^D$: $(1 - B^{12})$

Based on the SARIMA (1,0,1)(0,1,1)[12] model obtained, the demand pattern for omega chicken eggs is influenced by a combination of non-seasonal and seasonal factors. The forecast value is influenced not only by historical values from previous periods but also by short-term error components and seasonal error from one previous period (12 months).

This indicates that the demand for omega chicken eggs has indications of a seasonal pattern, so the SARIMA model is better able to represent the data pattern than a non-seasonal model. This finding aligns with Hyndman (2018), who states that SARIMA is effective for use on time series data with seasonal patterns that repeat periodically.

Table 2. Forecasting Model Accuracy Comparison

Product	Model	MAPE	MSE	MAD
Regular Chicken Egg	ARIMA (0,0,1)	4.2%	12,456.3	87.6
Omega Chicken Egg	SARIMA (1,0,1)(0,1,1)[12]	6.8%	28,934.7	156.2

The MAPE values for both models fall below 10%, indicating good forecasting accuracy (Hyndman & Athanasopoulos, 2018). The lower MAPE of the ARIMA model for regular eggs reflects the more stable demand pattern, while the slightly higher MAPE for omega eggs is attributable to seasonal demand fluctuations.

Inventory Control Using the EOQ Method

Economic Order Quantity (EOQ)

a. EOQ for Regular Chicken Egg

$$EOQ: \sqrt{\frac{2(94{,}595)(24{,}160)}{275.67}} = 245.4 = 245 \text{ kg} \quad (12)$$

Based on the calculation results, the optimal order quantity (EOQ) for regular chicken eggs is 245 kg per order.

b. EOQ for Omega Chicken Egg

$$EOQ: \sqrt{\frac{2(110{,}984)(24{,}160)}{275.67}} = 265.7 = 265 \text{ kg} \quad (13)$$

Based on the calculation results, the optimal order quantity (EOQ) for omega chicken eggs is 265 kg per order. The EOQ calculation results in this study show different optimal order quantities for the two products, which are influenced by the annual demand rate.

Safety Stock Calculation

a. Regular Chicken Egg

In calculating the safety stock for regular chicken eggs, the following data were obtained:

$$SS = Z \times \sigma_d \times \sqrt{L} \quad (14)$$

SS : *Safety stock*
Z : *Service level*
σ : *Standard deviation of demand*
L: *Lead time*

Thus, the safety stock value is obtained as follows:

σ_d: 7.4
Z: 1.65
L: 2 days

$$SS: 1.65 \times 7.4 \times \sqrt{2} = 17.27 \text{ kg} = 17 \text{ kg}$$

b. Omega Chicken Egg

In calculating the safety stock for omega chicken eggs, the following data were obtained:

$$SS = Z \times \sigma_d \times \sqrt{L} \quad (15)$$

SS : *Safety stock*
Z : *Service level*
σ : *Standard deviation of demand*
L: *Lead time*

Thus, the safety stock value is obtained as follows:

σ_d: 22.1
Z: 1.65
L: 2 days

$$SS: 1.65 \times 22.1 \times \sqrt{2} = 51.56 \text{ kg} = 52 \text{ kg}$$

Based on the calculations above, the safety stock that Distributor X must prepare for omega chicken eggs is 52 kg, while for regular chicken eggs, it is 17 kg. The results of this study indicate that omega chicken eggs have a higher safety stock value compared to regular chicken eggs. This condition aligns with the SARIMA modeling results for omega chicken eggs, which show fluctuations and indications of seasonal patterns in demand. The higher the demand variation for a product, the greater the need for safety stock to maintain service stability and anticipate demand uncertainty in the supply chain, as explained by (Barros et al., 2021).

***Reorder Point* (ROP)**

a. Regular Chicken Egg

The known data are as follows:

$ROP = d \times L + SS$ (16)

Where:

ROP : Reorder point.

d : Demand rate per unit time.

L : Lead time.

Then, the calculation is:

$$SS: 17 \text{ kg}$$
$$L: 2 \text{ days}$$
$$d: \frac{94{,}595}{360} = 262.76 \text{ kg/day}$$
$$ROP: (262.76 \times 2) + 17 = 542.52 \text{ kg} = 543 \text{ kg}$$

b. Omega Chicken Egg

The known data are as follows:

$$SS: 52 \text{ kg}$$
$$L: 2 \text{ days}$$
$$d: \frac{110{,}984}{360} = 308.29 \text{ kg/day}$$
$$ROP: (308.29 \times 2) + 52 = 668.58 \text{ kg} = 669 \text{ kg}$$

Based on the calculations above, Distributor X must reorder omega chicken eggs when the inventory level reaches 669 kg, while for regular chicken eggs, reordering should occur when the inventory reaches 543 kg.

Total Inventory Cost (TIC)

a. Total Inventory Cost Calculation

After obtaining the Economic Order Quantity (EOQ) value, the Total Inventory Cost was calculated to measure the total cost arising from the combination of ordering costs and holding costs. The total inventory cost is the cost that Distributor X will incur for economical ordering. The total inventory cost is calculated using the equation:

b. Total Inventory Cost for Regular Chicken Egg

The data used in calculating the total inventory cost are as follows:

$TIC = \frac{D}{Q}S + \frac{Q}{2}H$ (17)

d = Annual demand (kg)

a. Year 2026 = 94,393 kg

b. Year 2027 = 94,595 kg

c. Year 2028 = 94,595 kg

Q = *Economic Order Quantity* (EOQ) = 245 kg

S = Ordering cost per order = Rp 24,160

H = Holding cost per unit per year = Rp 275.67

The calculation results are described as follows:

a) TIC for 2026: $(\frac{94{,}393}{245} \times 24{,}160) + (\frac{245}{2} \times 275.67)$ = Rp 9,342,304

b) TIC for 2027: $(\frac{94{,}595}{245} \times 24{,}160) + (\frac{245}{2} \times 275.67)$ = Rp 9,359,317

c) TIC for 2028: $(\frac{94{,}595}{245} \times 24{,}160) + (\frac{245}{2} \times 275.67)$ = Rp 9,359,317

Based on the calculation results, the total inventory cost for regular chicken eggs during the 2026–2028 period using the Economic Order Quantity (EOQ) method is Rp 28,060,938.

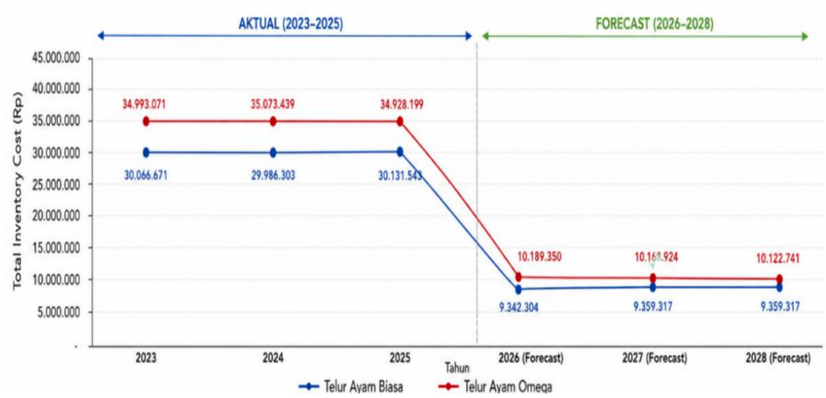

Figure 1. Comparison of Actual and Forecast TIC for Regular and Omega Chicken Egg Products for 2023-2028

The calculation results indicate that the total inventory cost for regular chicken eggs during the 2023–2025 period was approximately Rp29–30 million per year, while for omega chicken eggs it was around Rp34–35 million per year. Furthermore, the forecast results for 2026–2028 show a downward trend in total inventory costs for both products, indicating that the forecasting outcomes and inventory management calculations are projected to improve future inventory cost efficiency.

Through the integration of demand forecasting, EOQ, safety stock, total inventory cost, and reorder point (ROP), this study provides a more comprehensive view of inventory management. This approach can be used as a reference for UD. X in determining order quantities, maintaining stock availability, and reducing inventory costs more effectively. The results also show that the total inventory cost for omega chicken eggs is higher than that for regular chicken eggs, primarily due to a higher annual demand rate and a larger optimal order quantity. Overall, the integration of forecasting results, EOQ, safety stock, total inventory cost, and ROP demonstrates a structured and comprehensive inventory management framework.

Discussion

Inventory management is a crucial element in maintaining supply chain stability, especially for food distribution companies handling perishable products. Based on the research results, Distributor X still applies a conventional inventory management system, relying on experience and subjective estimates to determine order quantities and procurement timing. This condition often leads to mismatches between customer demand and available warehouse stock. At certain times, the company experiences stockouts, while at other times, inventory overstock occurs. This imbalance indicates that the inventory control system at Distributor X is not yet optimal and is not supported by a data-driven forecasting approach.

The bullwhip effect at Distributor X can be attributed to three primary operational factors specific to this company. First, the absence of a formal demand recording system means that ordering decisions are based on the owner's subjective assessment of market conditions rather than historical data analysis. Second, the practice of batch ordering—placing large orders when prices are perceived to be low—creates artificial demand spikes that are transmitted upstream to suppliers. Third, the lack of information sharing between Distributor X and its customer base (traditional market traders and grocery stores) results in delayed demand signals, amplifying variability. These factors collectively explain why the bullwhip effect values (1.4 for regular eggs and 1.3 for omega eggs) exceed the threshold parameter of 1.12, with regular eggs showing higher amplification due to a larger number of downstream customers and more fragmented ordering patterns.

This problem aligns with the theory proposed by Heizer (2020), which states that errors in estimating demand are a primary cause of inventory inefficiency in supply chains. When a company lacks an accurate forecasting system, ordering decisions tend to be based on intuition, increasing the risk of errors in determining inventory levels. In chicken egg distribution companies, this condition becomes more complex because eggs have a limited shelf life and are prone to quality degradation if stored for too long. Therefore, errors in inventory management not only increase operational costs but can also decrease product quality and customer satisfaction.

Furthermore, observation results show that coordination between customer demand and the distribution process is not yet optimal. The company does not have an integrated demand recording system, so changes in market demand patterns cannot be monitored quickly and accurately. This condition causes ordering decisions to often not match actual market needs. This phenomenon shows that the main problem at Distributor X is not only inventory quantity but also the decision-making system, which is not yet data-driven and unable to respond effectively to demand changes.

The occurrence of the bullwhip effect at Distributor X reflects structural weaknesses in information sharing and inventory decision-making rather than merely fluctuations in customer demand. The findings indicate that procurement decisions are still dominated by managerial intuition and periodic bulk purchasing instead of systematic demand forecasting. Consequently, relatively small variations in downstream demand are amplified into substantially larger procurement orders, generating inefficiencies throughout the supply chain. This interpretation supports the theoretical explanation proposed by Fransoo (2000), who argue that distorted demand information is one of the primary drivers of the bullwhip effect.

According to Fransoo (2000), the bullwhip effect occurs due to misinterpretation of demand information along the supply chain. In the context of this research, this phenomenon is influenced by forecasting inaccuracies, delays in demand information, and unstructured ordering policies. Additionally, Distributor X has not implemented a periodic demand monitoring system, so market fluctuations cannot be anticipated properly. This condition causes the company to place large orders when demand increases but experience stock buildup when demand falls.

The impact of the bullwhip effect on Distributor X is seen in increased storage costs, distribution imbalances, and the risk of product damage due to stockpiling. This finding aligns with research by Durán (2021), which states that the bullwhip effect in food supply chains leads to increased waste and distribution inefficiency. For chicken egg products, excess stock conditions can reduce product quality because eggs have a relatively short shelf life. Conversely, when the company experiences stock shortages, customers cannot obtain products as needed, potentially lowering customer satisfaction and market loyalty.

This research shows that the bullwhip effect not only impacts the company's operations but also affects the effectiveness of the entire supply chain. Therefore, the company needs an inventory management system capable of controlling demand fluctuations more accurately and systematically. One solution offered in this research is the application of forecasting based on historical data using ARIMA and SARIMA methods. Forecasting is a crucial approach to supporting inventory decisions (Mustika et al., 2025). In this study, the ARIMA method was used to predict demand for regular chicken eggs, while SARIMA was used for omega chicken eggs, which exhibit seasonal patterns. The selection of these two methods was based on the characteristics of the historical demand data analyzed through stationarity tests, ACF and PACF plots, and the model identification process.

The selection of different forecasting models for each product demonstrates that demand forecasting should be tailored to product characteristics rather than relying on a single forecasting technique. The relatively stable demand pattern of regular eggs allows a simpler ARIMA model to perform effectively, whereas the seasonal purchasing behavior of omega eggs requires a model capable of capturing recurring seasonal fluctuations. This finding highlights the importance of model selection based on demand characteristics, supporting Hyndman (2018), who emphasize that forecasting performance depends largely on the underlying data structure.

The application of ARIMA and SARIMA-based forecasting significantly improves the company's inventory planning accuracy. With forecasting, the company can estimate future demand more systematically so that ordering decisions are no longer based solely on intuition. Additionally, forecasting helps the company anticipate market demand fluctuations and determine more effective distribution strategies. The results of this study align with research by Klaharn (2024), which stated that SARIMA has high accuracy for seasonal demand data in the poultry industry. Research by Vo (2021) also showed that ARIMA can improve inventory control effectiveness in manufacturing industries with fluctuating demand patterns. However, this research offers novelty because it not only focuses on forecasting but also integrates forecasting results with inventory control strategies to minimize the bullwhip effect in the chicken egg distribution supply chain.

After obtaining the forecasting results, the research continued with inventory control analysis using the Economic Order Quantity (EOQ), safety stock, and reorder point (ROP) approaches (Trihudiyatmanto, 2017). This approach helps the company determine optimal order quantities, anticipate demand uncertainty, and maintain product distribution continuity. The integration of forecasting outputs with inventory control policies demonstrates that accurate demand prediction alone is insufficient to improve supply chain performance unless it is translated into operational decision-making. Forecast information becomes valuable only when it guides ordering frequency, replenishment timing, and inventory buffering strategies. Consequently, the combination of forecasting and EOQ-based inventory policies provides a practical mechanism for reducing unnecessary inventory accumulation while maintaining product availability under uncertain demand conditions.

These findings show that integrating forecasting with inventory control can significantly improve the company's operational efficiency. Harahap (2025) explain that the combination of forecasting and inventory control can help companies minimize inventory costs and improve distribution effectiveness. Compared with previous studies, this research extends existing knowledge by integrating three analytical perspectives within a single framework. Previous studies generally examined either forecasting accuracy, inventory optimization, or the bullwhip effect independently. In contrast, the present study demonstrates how forecasting accuracy directly influences inventory policy decisions and subsequently affects supply chain efficiency. This integrated perspective is particularly relevant for perishable food products, where forecasting errors immediately translate into inventory losses and quality deterioration.

A detailed comparison reveals both convergent and divergent findings with prior literature. The bullwhip effect values in this study (1.3–1.4) are consistent with findings by Durán (2021), who reported values of 1.2–1.5 in perishable food supply chains, but higher than those found by Lukmandono (2024) in salt distribution (1.1–1.2), likely because salt is a non-perishable commodity with more predictable demand. The MAPE values obtained (4.2% for ARIMA, 6.8% for SARIMA) compare favorably with Klaharn et al. (2024), who achieved 7–9% MAPE in poultry forecasting using SARIMA alone, suggesting that product-specific model selection improves accuracy. However, unlike Gamberini (2010), who found that Holt-Winters outperformed ARIMA in manufacturing contexts with strong trends, this study found ARIMA sufficient for regular eggs due to the absence of significant trend components. The difference can be explained by distinct demand characteristics of perishable food versus manufactured goods: egg demand is relatively stable with short-term shocks rather than sustained trends (Ali et al., 2012).

However, this research has several differences and novelties compared to previous studies. First, this research was conducted in the chicken egg distribution sector, which has perishable product characteristics, making inventory management more complex than for non-food products. Second, this research not only focuses on forecasting but also integrates bullwhip effect analysis, ARIMA/SARIMA forecasting, and inventory control using EOQ, safety stock, and ROP into one comprehensive research model. Third, this research emphasizes the relationship between forecasting results and inventory decisions to minimize demand distortion in the supply chain.

The contribution of this research to the literature lies in an integrative approach linking forecasting and inventory control in the context of food distribution in Indonesia. In addition to providing academic contributions, the results also have practical benefits, as they can serve as a basis for distribution companies to improve their inventory management systems and enhance supply chain efficiency. The application of ARIMA/SARIMA-based forecasting and inventory control through EOQ, safety stock, and ROP should positively impact the company's operations. With a more accurate forecasting system, the company can estimate market demand more precisely and reduce the risk of ordering errors. This leads to lower storage costs, improved distribution efficiency, and reduced risk of product damage due to stockpiling. Furthermore, the implementation of a more structured inventory control system helps improve service quality to customers. When the company can consistently maintain product availability, customer satisfaction also increases. In the long run, this condition can strengthen customer loyalty and enhance the company's competitiveness in the food distribution market.

Overall, the findings demonstrate that improving forecasting accuracy alone is insufficient to eliminate supply chain inefficiencies. Sustainable improvements require simultaneous enhancement of demand forecasting, inventory policy, and information sharing across supply chain members. Therefore, the integrated analytical framework proposed in this study may serve as a practical decision-support model for distributors managing perishable products under uncertain demand conditions. Beyond the case of Distributor X, the framework has the potential to be adapted by similar food distribution companies seeking to improve operational efficiency while minimizing the bullwhip effect.

CONCLUSION

This study analyzed inventory management practices at Distributor X by examining the bullwhip effect, identifying the most appropriate forecasting models, and developing inventory control strategies. The findings indicate that demand distortion in the company's supply chain is primarily driven by intuition-based ordering decisions rather than a data-driven forecasting system. ARIMA was identified as the most accurate forecasting model for regular chicken eggs, whereas SARIMA provided superior forecasting performance for omega chicken eggs based on MAPE, MSE, and MAD evaluation metrics. The integration of demand forecasting with EOQ (Economic Order Quantity), safety stock, and reorder point (ROP) enables more effective inventory planning, reduces the risk of stockouts, and improves inventory cost efficiency. These findings demonstrate that combining forecasting and inventory control provides an effective strategy for mitigating the bullwhip effect in perishable food distribution.

This research contributes to the supply chain management literature by proposing an integrated analytical framework that combines bullwhip effect measurement, product-specific demand forecasting, and EOQ-based inventory optimization for perishable food distribution. Practically, the proposed framework provides Distributor X with a data-driven decision-support system capable of replacing intuition-based inventory management and is projected to reduce total inventory costs by approximately 5–7% annually while maintaining a 95% service level through optimized safety stock and reorder point policies. Nevertheless, this study is limited to a single company and a three-year observation period. Future research should involve multiple distribution companies, extend the observation period, and compare additional forecasting techniques to improve the generalizability and robustness of the proposed framework.

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AUTHOR CONTRIBUTION STATEMENT

Author 1 was responsible for research design, data collection, data analysis, and manuscript writing. Author 2 supervised the research, provided methodological guidance, and edited the manuscript. Both authors read and approved the final version of the manuscript.

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