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Inventory Management Optimization of Snack to Minimize Days Sales Inventory (DSI) and Total Cost

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Abstract

This study aims to optimize snack inventory management in retail industry by minimizing Days Sales Inventory (DSI) and Total Cost (TC). The research begins with ABC Analysis using sales history from First Period (Weeks 1–21). The results show that 27 Class A products have DSI more than 35 days. These Class A products are forecasted for the Second Period (Weeks 22–52) using three methods: Holt-Winters, ARIMA (1,1,1), Random Forest Regression. Random Forest Regression becomes the best forecasting method, with MAE 42.4, MAPE 13.9%, and RMSE 46.7. The study calculates Safety Stock and Reorder Point for each Class A. The ordering schedule uses EOQ and POQ. Both EOQ and POQ reduce DSI and TC, but POQ provides more significant improvement. Using POQ method, DSI decreases from 111 to 71 days, while EOQ reduces it to 73 days. Annual TC decreases from 36.977.235 to 16.950.093, while EOQ produces 17.326.213. POQ gives 2 days faster DSI and saves 376,120 in annual TC vs EOQ. This study provides new perspective on weekly multi-product inventory control using Python and Microsoft Excel. Future research considers promotion effects, seasonal periods such as Christmas and Eid, and integration with ERP or IoT technology for multi-category data.

Keywords: *inventory management optimization, days sales inventory, demand forecasting, economic order quantity, periodic order quantity*

Abstrak

Penelitian ini bertujuan mengoptimalkan manajemen persediaan makanan ringan pada industri retail dengan meminimasi Days Sales Inventory (DSI) dan Total Cost (TC). Penelitian dimulai dengan ABC Analysis berdasarkan histori penjualan Periode Pertama (Minggu 1-21). ABC Analysis produk Kelas A dengan DSI lebih dari 35 hari berjumlah 27. Produk tersebut dilakukan peramalan untuk Periode Kedua (Minggu 22-52) dengan 3 metode, yaitu Holt-Winters, ARIMA (1,1,1) dan Random Forest Regression. Metode peramalan terbaik adalah Random Forest Regression dengan MAE 42,4; MAPE 13,9%; dan RMSE 46,7. Produk kelas A masing-masing dihitung Safety Stock dan Reorder Point. Penjadwalan pemesanan dibuat dengan metode EOQ dan POQ. EOQ dan POQ mampu menurunkan DSI dan TC. Namun, POQ memberikan hasil yang lebih signifikan. Dengan metode POQ, DSI turun signifikan dari 111 menjadi 71 hari, sedangkan EOQ 73 hari. Estimasi TC tahunan turun dari 36.977.235 menjadi 16.950.093, sedangkan TC dengan EOQ sebesar 17.326.213. POQ menghasilkan DSI 2 hari lebih cepat dan menghemat TC tahunan sebesar 376.120 dibanding EOQ. Penelitian ini berkontribusi memberikan perspektif baru terkait pengendalian persediaan dengan multiple produk secara mingguan dengan Python dan Microsoft Excel. Rekomendasi penelitian selanjutnya adalah mempertimbangkan promosi, periode seasonal seperti Natal dan Lebaran, serta mengintegrasikan dengan ERP or IoT technology untuk data multi kategori.

Kata Kunci: *optimasi manajemen persediaan, days sales inventory, peramalan permintaan, economic order quantity, periodic order quantity*

1. Introduction

Inventory management is a critical aspect of a company's operational success, particularly in maintaining the balance between product availability and the costs incurred from storage. Effective inventory control is essential to avoid excessive costs caused by overstocking as well as sales losses due to stockouts. Limited storage capacity presents a major challenge for the retail industry, especially for snack products that have limited shelf life and exhibit unstable and fluctuating demand patterns [1]; [2].

In the retail industry, particularly in the snack product category, the phenomenon of high Days Sales Inventory (DSI) can lead to substantial storage costs, increased risk of product damage, and higher likelihood of product expiration. DSI serves as an important indicator that must be evaluated to identify its root causes, as it significantly affects a company's financial flow on a monthly or annual basis. Ideally, products should be sold within the shortest possible time. Uncertain demand shifts in consumer preferences, and potential lost sales due to stockouts or overstocking represent real issues that must be addressed to improve the efficiency of inventory management [3]; [4].

Effective inventory control typically involves two key stages: a forecasting process to predict future needs and determining order quantities using quantitative methods such as Economic Order Quantity (EOQ) and Periodic Order Quantity (POQ), which both aim to minimize total inventory costs [5]; [6]. Various studies have shown that integrating forecasting methods with appropriate order quantity and scheduling models can produce more optimal inventory control by reducing the risk of overstocking and stockouts [7]; [8]. Furthermore, stock management methods often involve the use of safety stock and dynamic reorder points, adapted to the level of demand variability and lead time, to reduce the risk of untimely ordering [9]; [10]. Despite these developments, there remains a significant research gap regarding the holistic implementation of adaptive forecasting methods combined with EOQ and POQ models to optimize snack inventory management in the retail industry, particularly under conditions of highly fluctuating demand and high DSI levels [11]; [12].

This study aims to address this gap by developing an approach that integrates market-responsive forecasting techniques with EOQ and POQ models to determine optimal ordering quantities and scheduling. Thus, this research is expected to provide both practical and academic contributions, helping snack retail industry management improve inventory control efficiency while enriching the literature on quantitative methods in forecasting-based and optimization-based inventory management.

This study aims to determine the most suitable forecasting method for snack products. Furthermore, it compares DSI and inventory costs between the First Period using the existing approach and the Second Period using EOQ and POQ, as well as comparing DSI and cost differences between EOQ and POQ. This research provides weekly data for 52 weeks or 1 year. It gives new insights into maintaining inventory management by week with each Minimum Order Quantity (MOQ). This research also provides recommendations for the company and future studies. Data processing in this research combines Python and Microsoft Excel, where forecasting calculations are performed using Python and EOQ–POQ computations are performed using Microsoft Excel. This provides a new perspective that Microsoft Office can be effectively used to analyze small to medium-scale businesses with multiple product variations. The concept of evaluating DSI levels and their impact on inventory cost efficiency serves as a novel contribution to research in the snack retail industry, offering benefits to both the company studied and other similar industries.

2. Material and Methods

Material

This research focuses on snack products in the retail industry, categorized as fast-moving products such as extruded snacks, chips, and nuts, using sales and inventory data from 69 products during Week 1 to Week 21 of 2025. In addition, ordering cost, holding cost, purchase lead time, product price, and minimum order quantity (MOQ) data were also collected as the basis for forecasting and inventory control analysis.

Methods

Type of Research

This research focuses on a case study based on quantitative data, analyzed through a comparative approach [13]. The analysis process begins with ABC analysis of 69 snack products based on their percentage contribution to sales. Pareto concepts for products categorized into Class A (0–75%) or high sales contribution, Class B (75–95%) or moderate sales contribution, and Class C (95–100%) or low sales contribution. After classification, 27 products fall into Class A, contributing to 59% of total sales. These 27 products are then forecasted for the next 31-week period. Subsequently, ordering analysis is conducted using the EOQ and POQ methods.

Data Collection Techniques

The data used in this research consists of primary and secondary data, as explained below:

1. Primary Data
   Primary data are obtained through interviews with responsible personnel, discussing the challenges arising from high DSI levels, particularly for snack products, as well as their impact on holding costs and ordering costs.

2. Secondary Data
   Secondary data consist of historical sales data from Week 1 to Week 21 of 2025, beginning–ending inventory data, ordering cost, holding cost, purchase lead time, product price, and minimum order quantity (MOQ) [14].

Research Instruments

These tools are capable of providing information regarding evaluation of metric indicators or the smallest forecasting error, as well as determining the optimal order quantity and ordering period for each choosen product.

Research Flow

The research process is shown in Figure 1 that begins with problem identification, followed by the collection of primary and secondary data. Primary data were obtained through interviews and field observations. Secondary data include information of First Period The main instruments used in this research include statistical processing and forecasting by combining Python and Microsoft Excel software, consist of sales, purchase order quantities, opening stock, closing stock, lead time, and minimum order quantity (MOQ) from the First Period (Week 1-21). Sales data from the first period were categorized using ABC analysis. Sales data for the Second Period (Week 22-52) were projected using three forecasting methods, consist of Random Forest Regression, Holt-Winters, and ARIMA. The forecasting results were then evaluated to select the method with the lowest error as the best model. Based on the selected forecast, inventory control analysis was conducted using Economic Order Quantity (EOQ) and Periodic Order Quantity (POQ) [15]. The final stage of the research compares conditions in the first and second periods, as well as the outcomes of EOQ versus POQ implementation, focusing on Days Sales Inventory (DSI) and total costs before drawing conclusions.

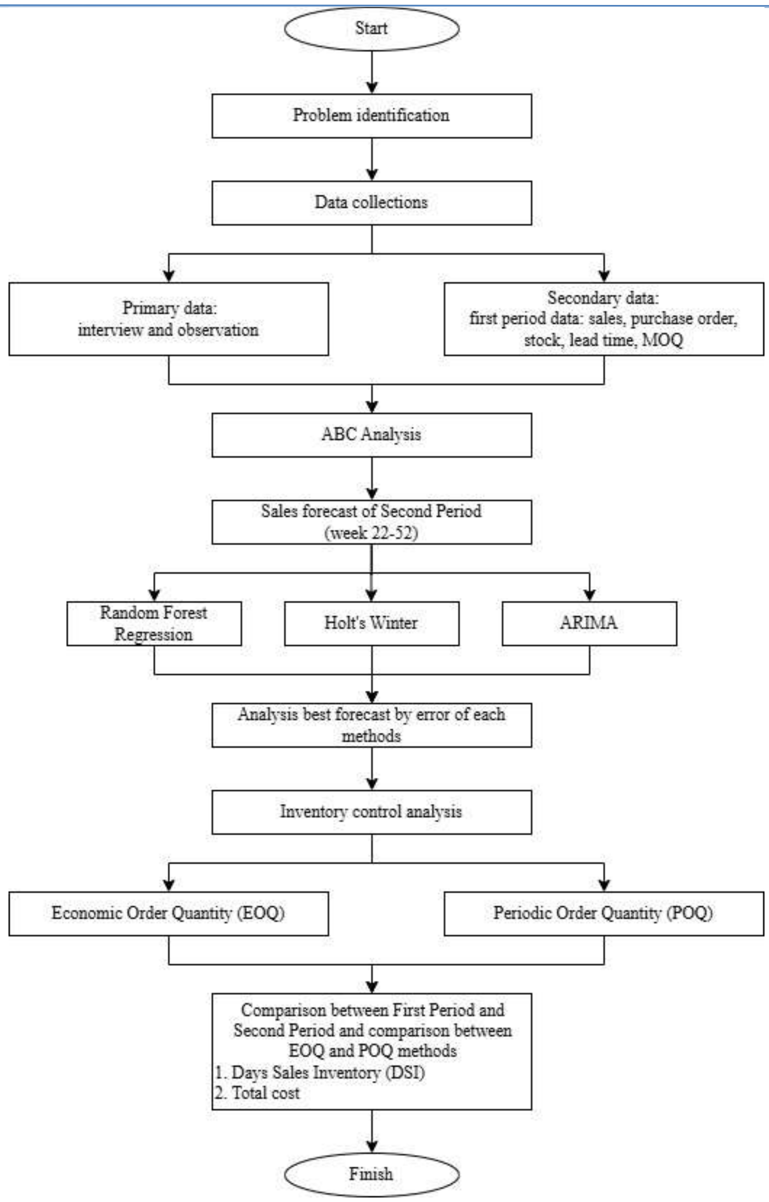

Figure 1. Flow Process Research

Data Analysis Techniques

1. ABC Analysis

   This research using Sales Contribution Percentage and Days Sales Inventory (DSI) to classify the 27 items product.

$$\%\,Sales\ Contribution\ = \frac{(Qty\ Sales\ per\ item)}{(Total\ Qty\ Sales\ per\ category)}\,x\ 100\% \quad ....(1)$$

$$Days\ Sales\ Inventory\ (DSI)\ = \frac{\frac{(Opening\ Stock+End\ Stock)}{2}}{Avg\ Sales\ per\ Day} ....(2)$$

2. Forecast methods: Random Forest Regression, Holt-Winters, ARIMA

   Here are key formulas for Random Forest Regression, Holt-Winters, and ARIMA models:

   - Random Forest Regression formulas often include regression equations such as linear regression:

$$y = \beta 0 + \beta 1x1 + \beta 2x2 + \ldots + \beta nxn + \epsilon \quad ....(3)$$

   and optimization methods like gradient descent for parameter estimation:

$$\theta = \theta - \alpha m1i = 1\sum_{i-1}^{m} m(h\theta(x(i)) - y(i))x(i) \quad ....(4)$$

- Holt-Winters exponential smoothing method formulas for level (ℓt), trend (bt), and seasonal component (st) use smoothing parameters α, β, γ:
  a. Level Update
  $$\ell t = \alpha \frac{yt}{S_{t-m}} + (1-\alpha)(\ell t - 1 + bt - 1) \text{ ....(5)}$$
  b. Trend update:
  $$bt = \beta(\ell t - \ell t - 1) + (1-\beta)bt - 1 \text{ ....(6)}$$
  c. Seasonal update:
  $$st = \gamma \frac{yt}{\ell t} + (1-\gamma)st - m \text{ ....(7)}$$
  d. Forecast:
  $$y^t + h = (\ell t + hbt)st - m + h \text{ ....(8)}$$

- ARIMA models combine autoregressive (AR), differencing (I), and moving average (MA) components [16]:
  a. General Forms:
  $$\phi p(B)(1-B)dyt = \theta q(B)\varepsilon t \text{ ....(9)}$$
  Where:
  B is the backshift operator, ϕp(B) is an AR polynomial, θq(B) is an MA polynomial, and d is the differencing order.

  b. Examples include ARIMA (0,2,2):
  $$Xt = 2Xt - 1 - Xt - 2 + (\alpha + \beta - 2)\varepsilon t - 1 + (1-\alpha)\varepsilon t - 2 + \varepsilon t \text{ ....(10)}$$

3. Safety Stock (SS)
Safety Stock is the extra inventory held to avoid stockouts due to variability in demand and supply.
$$Safety\ Stock = Z \times \sigma d \text{ ....(11)}$$

Where:
Z-score represents the number of standard deviations for the desired service level, e.g., 1.65 for 95% service level.
σd is the standard deviation of demand during lead time accounts for demand fluctuation during lead time. It itself is a number that shows how many standard deviations above the average are needed to reach a certain confidence level that stock will not run out. The higher the Z-score value, the larger the safety stock and the lower the risk of stock outs. Examples of Z-score for common confidence levels are 1.28 (90%), 1.65 (95%), and 1.96 (97.5%).

4. Reorder Point (ROP)
$$ROP = (Avg\ Sales\ per\ Day\ x\ Lead\ Time) + Safety\ Stock \text{............(12)}$$

5. Holding Cost (H)
The cost of carrying one unit of inventory per period.
$$Annual\ Holding\ Cost = H \cdot \frac{Q}{2} \text{............(13)}$$
Where:
H is holding cost per unit per year, Q/2 is the average inventory level.

6. Ordering Cost (S)
The cost incurred every time an order is placed.
$$Annual\ Ordering\ Cost = S \cdot \frac{D}{Q} \text{ ....(14)}$$
Where:
S is the ordering cost per order, D is the annual demand, Q is the order quantity.

7. Economic Order Quantity (EOQ)

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Calculating the optimal order quantity that minimizes the total cost of ordering and holding inventory using the formula[17]:

$$EOQ = \sqrt{\frac{2DS}{H}} \text{ ....(15)}$$

Where:
D is the annual demand, S is the ordering cost per order, and H is the holding cost per unit per year.

8. Periodic Order Quantity (POQ)
Determines the optimal order time interval based on the Economic Order Quantity (EOQ) [15].
   - Determines order period (T):

$$T = \frac{EOQ}{D} \text{ .... (16)}$$

   Where:
   T is the order period interval (per year/month/week), EOQ is the Economic Order Quantity, and D is the demand sales (per year/month/week).

   - Calculates order quantity per each period (Qt):

$$Qt = Dt \cdot T \text{ ....(17)}$$

   Where:
   Qt is the order quantity for period-t, and Dt is the forecast demand.

9. Total Inventory Cost (TC)

$$TC = \left(\frac{D}{Q}\right) \cdot S + \left(\frac{Q}{2}\right) \cdot H \text{ ....(18)}$$

Where:
Q is the quantity, D is the annual demand, S is the ordering cost per order, and H is the holding cost per unit per year.

10. The analysis evaluates the effectiveness of inventory control by measuring reductions in DSI and improvements in cost efficiency[18][19].

3. Results and Discussion

This research focused on finding strategies for inventory management of snack products to minimize cost and Days Sales Inventory (DSI). It started with analysis of products using ABC Analysis. Then, the selected products will be forecasted by three methods. Best forecast will be analyzed by Safety Stock, Reorder Points, EOQ and POQ Method.

ABC Analysis

Table 1 presents an ABC analysis of snack products, which categorizes snack products based on their relative importance, typically measured by their contribution to sales of total Snack. The analysis divides the products into three main classes: A, B, and C. Class A represents the most vital products, following the pareto where a small percentage of items contributes to a large percentage of sales. The pareto range for this class is 0-75% (meaning the first 75% of cumulative sales), accounting for a substantial 75% of the total sales contribution. Overall, Class A includes 38 total products that make the majority contribution of sales (75%). This class is further segmented by the DSI (Days Sales Inventory) metrics.

- Products with DSI > 35 days include 27 products and contribute 59% of sales.
- Products with DSI < 35 days include 11 products and contribute 18% of sales.

Class B represents the mid-range of importance. They cover the 75-95% range in the Pareto distribution, contributing between 15-20% to total sales. This class contains 18 products across All DSI values, meaning they are moderately important and require routine management, but not the intensive focus given to Class A. Class C products are the least critical in terms of sales contribution, covering the 95-100% Pareto range. These 13 products across All DSI contribute only 5-10% of total sales.

This research is focused on the 27 products of Class A with a DSI > 35 days. By focusing on these items, this research will have a significant impact on reducing the total DSI of snacks.

Table 1. ABC Analysis

Class	Pareto Range	Contribution Sales Range	DSI	Total Products (item)	% Contribution Sales
A	0-75%	75%	DSI > 35	27	59%
			DSI < 35	11	18%
B	75-95%	15-20%	All DSI	18	16%
C	95-100%	5-10%	All DSI	13	7%
		Total		**69**	**100%**

Source: Processed data (2025)

Sales Forecast

Class A data was forecasted to estimate sales for the second period. The historical data used consists of actual sales from the First Period (week 1–21), which exhibit several characteristics, including: time dependency, where sales in a given week are influenced by sales in the preceding week; the presence of trends and fluctuations, indicated by non-constant increases and decreases in sales values; and a non-linear sales pattern, shown by sudden sharp increases in demand during certain weeks followed by declines in others. These characteristics indicate that the historical sales data is suitable for testing using three different forecasting methods. The ARIMA method can capture autoregressive and moving average patterns; the Holt-Winters method can capture trends even in the absence of seasonal patterns; and the Random Forest Regression method is able to detect non-linear patterns with complex interactions across lags. Subsequently, sales forecasting for the Second Period or next 31 weeks (week 22-52) was performed using these methods, and the resulting error evaluation metrics are presented in **Table 2**.

Based on the evaluation results of the three forecasting methods, Random Forest Regression demonstrates the best performance compared to Holt-Winters and ARIMA. This is indicated by its lowest error values, with a Mean Absolute Error (MAE) of 42.4, a Mean Absolute Percentage Error (MAPE) of 13.9%, and a Root Mean Squared Error (RMSE) of 46.7. In contrast, Holt-Winters shows the highest error levels, with an MAE of 128.7, a MAPE of 35.7%, and an RMSE of 143.7, making it the least suitable method for this dataset. The ARIMA (1,1,1) model falls in the intermediate position, producing an MAE of 60.4, a MAPE of 18.4%, and an RMSE of 66.2. Therefore, Random Forest Regression is selected as the most accurate forecasting model, as it generates the smallest errors and delivers more reliable predictions.

In addition, Random Forest Regression demonstrates superior performance because it can capture the non-linear patterns present in snack product sales, which fluctuate sharply and tend to move up and down in a volatile behavior that cannot be adequately explained by linear models. This method also leverages sales relationships from previous weeks (lag1–lag5), allowing the model to learn from a richer historical memory compared to classical methods. Furthermore, it does not require the assumption of stationarity, enabling the model to work effectively directly on the raw data.

Table 2. Forecasting of Second Period

Methods	Metrics Evaluation		
	Mean Absolute Error (MAE)	Mean Absolute Percentage Error (MAPE)	Root Mean Squared Error (RMSE)
Random Forest Regression	42.4	13.9%	46.7
Holt-Winters	128.7	35.7%	143.7
ARIMA (1,1,1)	60.4	18.4%	66.2

Source: Processed data (2025)

Safety Stock (SS)

Safety stock is calculated for each individual product of Class A. The data details are shown in **Table 3**. Lead time of each products are constant. Based on the agreement between the retailer and the supplier, the expected service level is 85%, resulting in a Z-score of 1.04. The data details are shown in **Table 3**. Example for AA product, safety stock is calculated by Z-score × σd. Z-score is 1,04, and σd is calculated from sales week 1-52 using formula STDEV in Microsoft Excel. The σd result is 13 units. Calculation of safety stock resulting in 14-unit products.

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Reorder Point (ROP)

The reorder point is calculated for each individual product of Class A. The data details are shown in **Table 3**. Example for AA product, quantity ADS is 3 unit/day, safety stock is 14 units, and lead time is 2 days. The calculation of ROP is (3*2) +14 and resulting in 20 units. Determining the ROP should be conducted in proper calculation due to will be impact toward DSI in the end.

Table 3. Product Name, Safety Stock, and Reorder Point

Product Name	Opening Stock (Unit)	End Stock (Unit)	Avg Sales/Day (Unit)	MOQ (Unit)	Lead Time (Days)	Safety Stock (Unit)	Reorder Point (Unit)
AA	195	72	3	12	2	14	20
AB	241	138	4	12	2	20	28
AC	124	107	3	12	3	6	15
AD	213	88	3	20	3	23	32
AE	23	252	2	20	3	9	15
AF	104	209	1	12	2	10	12
AG	310	289	2	24	2	8	12
AH	120	189	1	24	2	10	12
AI	313	199	2	20	1	11	13
AJ	222	249	1	12	2	7	9
AK	381	266	2	24	2	5	9
AL	317	295	1	24	2	9	11
AM	328	157	2	12	1	10	12
AN	256	106	2	12	1	3	5
AO	208	98	2	12	3	9	15
AP	103	292	1	12	3	8	11
AQ	299	156	2	6	3	9	15
AR	328	199	2	12	2	6	10
AS	340	217	2	12	2	4	8
AT	53	104	2	6	1	7	9
AU	165	39	2	12	2	3	7
AV	296	214	1	6	2	3	5
AW	329	176	2	6	2	4	8
AX	29	241	9	12	1	40	49
AY	42	75	1	12	2	5	7
AZ	185	155	1	12	2	4	6
BA	96	185	1	20	1	2	3

Source: Processed data (2025)

Holding Cost and Ordering Cost

Holding and Ordering cost should be determine before calculate the EOQ because both cost are basic components in the calculation. The purpose in EOQ is to shaping an efficient procurement strategy and designed to balance these two opposing costs so that total inventory cost can be minimized. Holding cost pushes companies to order smaller quantities to avoid excessive storage costs. Ordering cost pushes companies to order larger quantities to reduce order frequency. The company has been determined holding cost around 20% from product value and 4% for Ordering Cost per purchase price per product.

Economic Order Quantity (EOQ)

The EOQ calculation is performed for each product to determine the order quantity. Then, this quantity is combined with the reorder point to identify in which week the product needs to be reordered. Example for product AA, demand forecast Second Period is 536 unit, holding cost is IDR 5.577, ordering cost is IDR 1.900. EOQ calculation result of AA is 56 and it is rounded to MOQ (12 units), resulting in an EOQ of 60 units. The order qty is fixed for all ordering time.

$$\sqrt{\frac{2DS}{H}} = \sqrt{\frac{2 * 536 * 5.577}{1.900}} = 56\ units \approx 60\ units$$

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With reorder point 20 units, product AA will be reordered when weekly closing stock is under 20 units. The reorder time (**Figure 2**) is at week 25, 30, 33, 37, 40, 43, 46, 49, and 52. Frequency order of Second Period is 9 times.

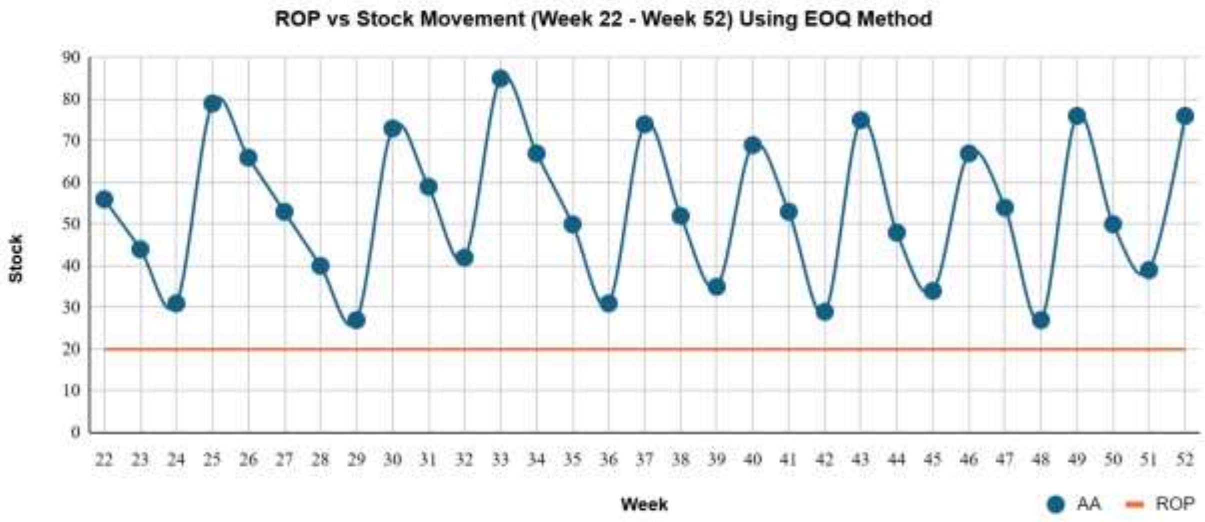

Figure 2. Stock Movement Product AA Using EOQ Method
Source: Processed data (2025)

The comparison between the First Period using the existing method and the Second Period using EOQ shows significant improvements in inventory efficiency and cost reduction in Table 4. Closing stock of First Period becomes opening stock of Second Period. Closing stock is reduced by IDR 32.079.500. DSI drops from 111 days to 73 days, reflecting a 38-day reduction in how long inventory stays in warehouse. Total cost of First Period (21 weeks) is IDR 14.933.114, meanwhile total cost of the Second Period (31 weeks) is IDR 10.329.088, resulting in savings of IDR 4.604.026 with gap 10 weeks. Estimated annual cost drops significantly from IDR 36.977.235 to IDR 17.326.213, representing an annual savings of IDR 19.651.022. Overall, the EOQ method delivers substantial improvements in DSI, stock efficiency, and cost savings compared to the existing approach.

Table 4. Comparison Between Existing and EOQ Method

Aspect	1st Period (Existing Method)	2nd Period (EOQ)	Gap
Opening Stock (IDR)	67.238.000	63.050.000	-4.188.000
Closing Stock (IDR)	63.050.000	32.079.500	-30.970.500
ADS (IDR)	586.570	655.400	68.830
DSI (Days)	111	73	-38
Total Cost (IDR)	14.933.114	10.329.088	-4.604.026
Estimated Annual Cost (IDR)	36.977.235	17.326.213	-19.651.022

Source: Processed data (2025)

Periodic Order Quantity (POQ)

Calculation of POQ begins with T (Formula 16). T is the order period interval (per 31 weeks), EOQ is the Economic Order Quantity of 31 weeks, and D is the demand sales (per 31 weeks). Example, product AA has EOQ 60 units, demand sales is 536 units. T of AA is 3,47 and rounded up to 4. It means ordering will be held every 4 weeks.

$$T = \frac{EOQ}{D} = \frac{60}{\frac{536}{31}} = 3.47 \approx 4$$

Because this product has high opening stock, scheduling order started from first reorder point of EOQ. After first reorder, the product will be ordered every 4 weeks within 31 weeks period forward, resulting in 7 times repetition. The first reorder point is on week 25. Next order times are week 29, 33, 37, 41, 45, 49. Order qty of POQ Method depends on demand of 4 weeks. Order qty of week 25 is 60. It

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calculated from forecast demand of week 25-28 (12, 13, 13, 13). Total demand is 51 units and rounded up to MOQ (12 units) and order quantity for week 25 becomes 60 units. Stock movement of Product AA is shown in **Figure 3**.

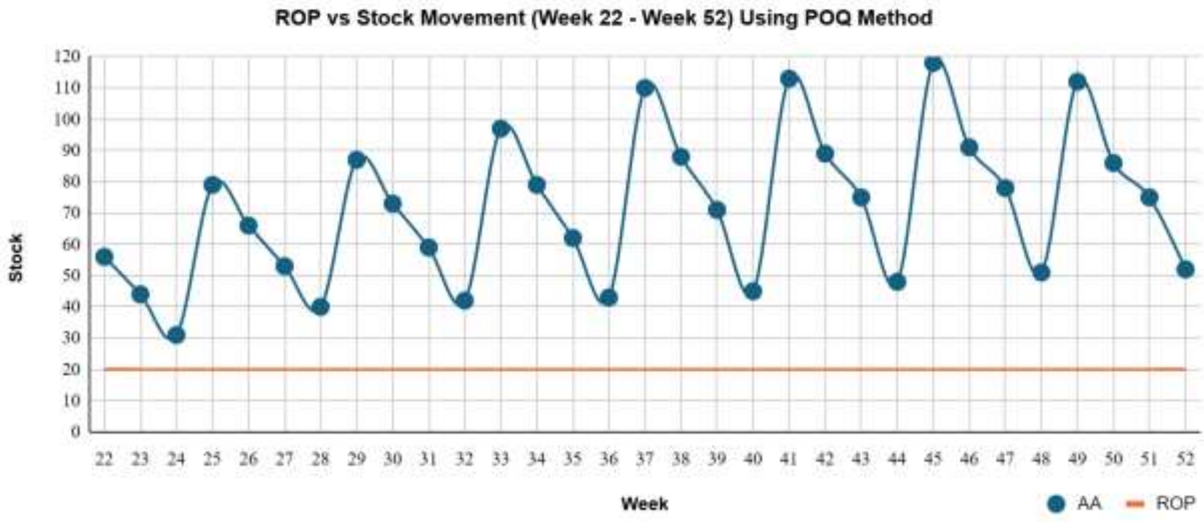

Figure 3. Stock Movement of Product AA Using POQ Method
Source: Processed data (2025)

The comparison between the First Period using the existing method and the Second Period using POQ shows significant improvements in inventory efficiency and cost reduction Table 5. Closing stock of First Period becomes opening stock of Second Period. Closing stock is reduced by IDR 32.554.100. DSI drops from 111 days to 71 days. reflecting a 40-day reduction in how long inventory stays in warehouse. Total cost of First Period (21 weeks) is IDR 14.933.114, meanwhile total cost of the Second Period (31 weeks) is IDR 10.104.863. resulting in savings of IDR 4.828.251 with gap 10 weeks. Estimated annual cost drops significantly from IDR 36.977.235 to IDR 16.950.093, representing an annual savings of IDR 13.290.256. Overall, the POQ method delivers substantial improvements in DSI, stock efficiency, and cost savings compared to the existing approach.

Table 5. Comparison Between Existing and POQ Method

Aspect	1st Period (Existing Method)	2nd Period (POQ)	Gap
Opening Stock (IDR)	67.238.000	63.050.000	-4.188.000
Closing Stock (IDR)	63.050.000	30.495.900	-32.554.100
ADS (IDR)	586.570	655.400	68.830
DSI (Days)	111	71	-40
Total Cost (IDR)	14.933.114	10.104.863	-4.828.251
Estimated Annual Cost (IDR)	36.977.235	16.950.093	-20.027.142

Source: Processed data (2025)

Comparison between EOQ and POQ

Both EOQ and POQ are calculated to each product in Class A for both order quantity, frequency order, and interval order. The differences between EOQ and POQ are that EOQ has a fixed order quantity, then the frequency order and interval order based on reorder point. Meanwhile, POQ has a fixed interval order time, then the order quantity is calculated based on demand forecast during interval order. The differences between the two methods are shown in **Table 6**.

Table 6. Comparison Between POQ and EOQ in Second Period per Product

Item Name	EOQ			POQ		
	Order Qty (Unit)	**Freq Order**	**Interval Order (Week)**	**Order Qty (Unit)**	**Freq Order**	**Interval order (Week)**
AA	60	9	Based on ROP	Based on forecast during interval period	7	4
AB	72	8			8	4
AC	60	10			10	3
AD	80	5			5	6
AE	60	3			3	6
AF	24	0			0	24
AG	96	1			1	11
AH	48	0			0	21
AI	80	0			0	15
AJ	24	0			0	12
AK	120	2			2	10
AL	72	0			0	21
AM	72	1			1	11
AN	84	3			2	10
AO	48	2			2	9
AP	12	0			0	9
AQ	36	4			3	5
AR	84	2			2	9
AS	84	3			3	7
AT	24	6			6	4
AU	108	3			3	13
AV	42	0			0	9
AW	48	5			5	4
AX	108	23			15	2
AY	48	4			4	7
AZ	36	0			0	16
BA	40	0			0	20

Source: Processed data (2025)

The comparison between the EOQ and POQ methods in the Second Period shows that both approaches are impactful to DSI and cost compared to Existing Method (**Table 8**). **Table 7** shows that the POQ method demonstrated greater efficiency and cost-effectiveness across nearly all measured aspects. Specifically, POQ resulted in a lower Closing Stock (IDR 30,495,900 vs. IDR 32,079,500). Furthermore, POQ proved to be more efficient in managing inventory, reducing the Days Sales in Inventory (DSI) to 71 days, which is 2 days faster than EOQ. DSI is still 70s days because opening stocks of Second Period are mostly high. The implementation of POQ for the new year after the second period is expected to reduce the DSI again so that it will remain stable at around 30-40 days. Most importantly, POQ recorded a lower Total Cost (IDR 10,104,863 vs. IDR 10,329,088) and a substantially lower Estimated Annual Cost (IDR 16,950,093 vs. IDR 17,326,213), resulting in an estimated annual saving of IDR 376,120 compared to EOQ. Therefore, the data strongly suggests that POQ is the more financially advantageous method for inventory management in the second period where the ordering scheme is a fixed order time interval and the order quantity follows from demand, suitable for fluctuating demand as in this article [15]; [20].

Table 7. Comparison Total Snack Between POQ and EOQ in Second Period

Aspect	2nd Period (EOQ)	2nd Period (POQ)	Gap (POQ-EOQ)
Opening Stock (IDR)	63.050.000	63.050.000	0
Closing Stock (IDR)	32.079.500	30.495.900	-1.583.600
ADS (IDR)	655.400	655.400	68.830
DSI (Days)	73	71	-2
Total Cost (IDR)	10.329.088	10.104.863	-224.225
Estimated Annual Cost (IDR)	17.326.213	16.950.093	-376.120

Source: Processed data (2025)

Table 8. Comparison Total Snack Between First Period (Existing), POQ and EOQ in Second Period

Aspect	1st Period (Existing Method)	2nd Period (EOQ)	2nd Period (POQ)
Opening Stock (IDR)	67.238.000	63.050.000	63.050.000
Closing Stock (IDR)	63.050.000	32.079.500	30.495.900
ADS (IDR)	586.570	655.400	655.400
DSI (Days)	111	73	71
Total Cost (IDR)	14.933.114	10.329.088	10.104.863
Estimated Annual Cost (IDR)	36.977.235	17.326.213	16.950.093

Source: Processed data (2025)

4. Conclusion

Second Period Data forecasted by three methods. Random Forest Regression achieved the lowest error values, consisting of MAE 42.4, MAPE 13.9%, and RMSE 46.7. It indicates that Random Forest Regression has superior performance compared to Holt-Winters and ARIMA. Therefore, Random Forest Regression is selected as the most accurate and reliable forecasting model for this research.

The implementation of EOQ and POQ in the Second Period successfully improves inventory performance compared to the existing method in the First Period, shown by a reduction in closing stock and a decrease in DSI. POQ proved to be lower DSI and more cost-effective. DSI of POQ method is lower 2 days dan EOQ (71 vs 73). Total cost of POQ method is lower IDR 224.225 than EOQ, then estimated annual cost is -376.120 than EOQ

Recommendations for future research include considering the effects of promotions and seasonal periods, such as Christmas-New Year and Ramadan-Eid, as well as utilizing other simulation-based software for a larger number of products and use integration with ERP or IoT technology for multi-category data.

5. Abbreviations

DSI	Days Sales Inventory
EOQ	Economic Order Quantity
POQ	Periodic Order Quantity
MOQ	Minimum Order Quantity
ROP	Reorder Point
ADS	Average Daily Sales
SS	Safety Stock
TC	Total Cost
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
RMSE	Root Mean Squared Error

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