



Integrated ABC–EOQ and Monte Carlo Simulation for Inventory Cost and Service Level Evaluation

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Abstract—This study proposes an integrated approach combining ABC classification, Economic Order Quantity (EOQ), and Monte Carlo simulation to evaluate inventory performance under stochastic demand conditions in a palm oil processing plant. ABC classification identified 32 category A items that contribute significantly to total inventory value and require priority control. EOQ analysis was applied to determine optimal order quantity, followed by safety stock and reorder point calculations. A 1,000-iteration Monte Carlo simulation was used to assess inventory performance in the event of random demand. According to the simulation results, the average service level is roughly 0.88, and the stockout probability runs from 0.000 to 0.189, which corresponds to service level values between 0.811 and 1.000. Depending on the parameters of demand, the mean inventory cost ranges from roughly Rp 7,764 to Rp 1,281,248. The EOQ-based policy lowers inventory costs by roughly 15% to 29%, with an average savings of almost 22% when compared to the current policy, according to a comparison of total inventory costs. These results demonstrate that the integrated approach provides simultaneous information on inventory cost and service level under stochastic demand conditions.

Keywords: Inventory Management, ABC Classification, EOQ, Monte Carlo Simulation, Intermittent Demand

1. INTRODUCTION

In the manufacturing and processing sectors, inventory management is essential to maintaining business operations. To ensure uninterrupted production processes, the supply of necessary materials and components must be kept at an ideal level. A number of operational issues, such as high stock levels, higher holding costs, or shortages of essential commodities that could interfere with production, can result from ineffective inventory management. Inventory control becomes even more crucial in industrial settings where machinery plays a major role since equipment dependability is dependent on the availability of replacement parts. Production downtime may result from equipment maintenance being delayed if spare parts are not available when needed. Consequently, businesses need to put in place an efficient inventory management system that strikes a balance between cost effectiveness and inventory availability. However, because businesses frequently deal with a huge number of commodities with varying levels of importance and demand patterns, inventory management is not an easy process. Companies frequently keep a wide variety of inventory products, yet just a tiny percentage of them make up a sizable share of the overall inventory value. This calls for a methodical strategy that enables businesses to determine which issues need more management focus.

The Always Better Control (ABC) classification approach is one popular strategy for inventory priority. By classifying inventory items into three groups according to their relative relevance and annual consumption value, ABC analysis helps businesses concentrate their control efforts on high-value goods while using less complicated control mechanisms for less important items. Organizations can allocate resources more efficiently and enhance overall inventory management performance by using this classification approach [1][2][3] [4].

In order to reduce overall inventory expenses, businesses must decide on the ideal order amount after identifying key inventory items. To find the most inexpensive order size that combines ordering and holding costs, the Economic Order Quantity (EOQ) model is frequently utilized. By using EOQ, businesses can maintain adequate inventory levels while minimizing needless ordering frequency and avoiding high storage expenses. According to earlier research, when used correctly in industrial settings, the EOQ approach can dramatically lower overall inventory costs and boost operational effectiveness [5][6][7].



The problem faced by the company is that the inventory level of frequently used spare parts is not optimal, as stockouts occur frequently. This condition increases the frequency of ordering and leads to higher ordering costs. In addition, spare parts inventory is not well controlled due to fluctuating and uncertain demand patterns. Demand uncertainty makes it difficult for the company to determine appropriate order quantities and reorder timing, which may result in either excess inventory or insufficient stock.

This situation is particularly critical in a palm oil mill, where spare parts availability plays an important role in maintaining operational continuity. Any shortage of critical spare parts can disrupt processing activities and potentially lead to downtime, which may affect production performance. On the other hand, excessive inventory can increase holding costs and lead to inefficient capital utilization. Therefore, an effective inventory management system is required to maintain optimal spare parts availability under uncertain demand conditions. To address this issue, it is necessary to apply inventory prioritization, determine optimal order quantities, and evaluate inventory policies under stochastic demand conditions. These approaches can help ensure spare parts availability while minimizing total inventory costs and maintaining operational efficiency in palm oil mill operations.

Additionally, a number of studies have demonstrated that combining EOQ with ABC classification can enhance inventory control effectiveness. While EOQ establishes the best ordering strategy for those goods, ABC categorization enables companies to identify priority items. With this combination, businesses can minimize total inventory expenditures while concentrating inventory control efforts on the most important items [8]. Even while these techniques work well, classic EOQ models typically assume deterministic demand and constant lead time, which may not accurately reflect actual operating settings where demand frequently varies and contains uncertainty. In actuality, operational variables, maintenance plans, and unforeseen equipment malfunctions can all affect inventory demand.

However, the integration of ABC classification and EOQ alone may not be sufficient to handle demand uncertainty in real operational environments, particularly in maintenance spare parts inventory. In order to overcome this restriction, inventory policies under conditions of unpredictable demand might be assessed using simulation approaches. By creating arbitrary demand scenarios and assessing the ensuing inventory performance through multiple simulation trials, Monte Carlo simulation is frequently used to represent uncertainty. Under stochastic situations, this method enables researchers to estimate key performance metrics like service level, stockout likelihood, and total inventory cost [9].

Table 1. Research Gap of Previous Studies

No	Author	Year	Industry / Case	ABC	EOQ	Monte Carlo	Gap
1	Leepaitoon & Bunternghit	2019	Retail store	✓	–	✓	No EOQ integration
2	Busola et al.	2020	Bakery industry	✓	✓	–	No uncertainty simulation
3	Rizqi & Khairunisa	2020	Leather craft SME	–	–	✓	No classification
4	Patriarca et al.	2020	Perishable products	–	✓	✓	No ABC classification
5	Wulandari & Indrianto	2021	Plastic packaging	–	✓	✓	No item prioritization
6	Emar et al.	2021	Computer spare parts	✓	✓	–	No stochastic evaluation
7	Thiantravan	2021	Food repackaging	✓	✓	✓	No service level analysis
8	Andoaga-Mejia et al.	2023	MSME retail	✓	–	✓	No EOQ model
9	Rahmadini et al.	2023	Pharmaceutical vaccine	–	✓	✓	No classification stage
10	Ayhuasi & Gutierrez	2023	Metalworking SME	✓	✓	✓	No cost variability analysis
11	Amani & Okdinawati	2023	Telecommunication tower	✓	✓	–	No uncertainty modeling
12	Augusto et al.	2024	Automotive spare parts	✓	–	✓	No EOQ optimization

13	Farisan et al.	2025	Mall escalator spare parts	–	–	✓	No classification & EOQ
14	This Study	2026	Industrial inventory	✓	✓	✓	Integrated evaluation

Table 1 presents a comparison of earlier research. The table provides an overview of how ABC categorization, EOQ optimization, and Monte Carlo simulation are used in various sectors and research settings. The main focus of early research was on utilizing Monte Carlo simulation to handle demand uncertainty. For instance, [10] used ABC classification in conjunction with Monte Carlo simulation in a retail setting, but they did not include EOQ optimization. In a similar vein, [11] used Monte Carlo simulation in a small and medium-sized leather craft business without using optimization and classification techniques. EOQ optimization started to be included in later research. [12] and [13] combined EOQ with ABC categorization in the computer spare parts and bread industries, respectively. These experiments showed gains in ordering and inventory priority, but they did not take demand unpredictability into account. In the perishable goods and plastic packaging industries, further research like [14] and [15] coupled EOQ and Monte Carlo simulation. These methods dealt with stochastic demand, but they lacked mechanisms for prioritizing important goods. More recent research has tried to integrate several strategies. In various industrial settings, [16][17] and [18] used combinations of ABC classification, EOQ, and simulation. In terms of performance evaluation, the integration was still restricted, and some studies primarily addressed cost reduction without doing a thorough service level study. While [19] and [20] focused on simulation-based evaluation, they did not fully integrate categorization and optimization.

Additionally, a number of recent research, such as [21] and [9], used partial approaches based on the case study, such as escalator spare parts and telecommunication infrastructure. These studies emphasize how crucial it is to deal with demand uncertainty, but they still lack a thorough framework that combines simulation, optimization, and categorization all at once. The majority of earlier research uses ABC classification, EOQ, or Monte Carlo simulation alone or in partial combinations, as Table 1 illustrates. In many different businesses, the simultaneous integration of Monte Carlo simulation, EOQ optimization, and ABC categorization is still comparatively rare. In order to assess inventory performance more thoroughly, especially in terms of inventory cost and service level under stochastic demand situations, this study suggests an integrated strategy that combines these three methodologies. Therefore, this study aims to develop and evaluate an integrated inventory management approach combining ABC classification, Economic Order Quantity (EOQ), and Monte Carlo simulation for spare parts inventory in a palm oil processing plant. Specifically, the study aims to: (1) classify spare parts according to their annual consumption value using ABC analysis; (2) determine the optimal order quantity, safety stock, and reorder point for Category A items using the EOQ approach; and (3) evaluate inventory performance under stochastic demand conditions using Monte Carlo simulation based on stockout probability, service level, mean inventory cost, and cost variability.

2. RESEARCH METHODOLOGY

2.1 Research Framework (Flowchart)

This study's research methodology combines Monte Carlo simulation, ABC classification, and Economic Order Quantity (EOQ) to assess inventory performance in the context of stochastic demand. The process starts with gathering inventory data, then moves on to item priority, determining the ideal order number, and simulation-based evaluation. Figure 1 shows the general framework for the research.

Inventory data gathering, comprising demand, unit cost, ordering cost, holding cost, and lead time characteristics, is the first step in the research process, as seen in Figure 1. The ABC classification is based on the annual consumption value (ACV), which is computed using these facts. Because category A items are the most important inventory items, they are chosen for additional examination.

The ideal order amount is then determined by calculating the Economic Order Quantity (EOQ). In order to guarantee inventory availability throughout lead time, safety stock and reorder point quantities are then calculated. To assess inventory performance under stochastic demand conditions, a Monte Carlo simulation is run after the inventory parameters have been established. For every iteration, demand during lead time is computed and random demand values are generated. Stockout situations are checked by the simulation, and the outcomes are recorded appropriately

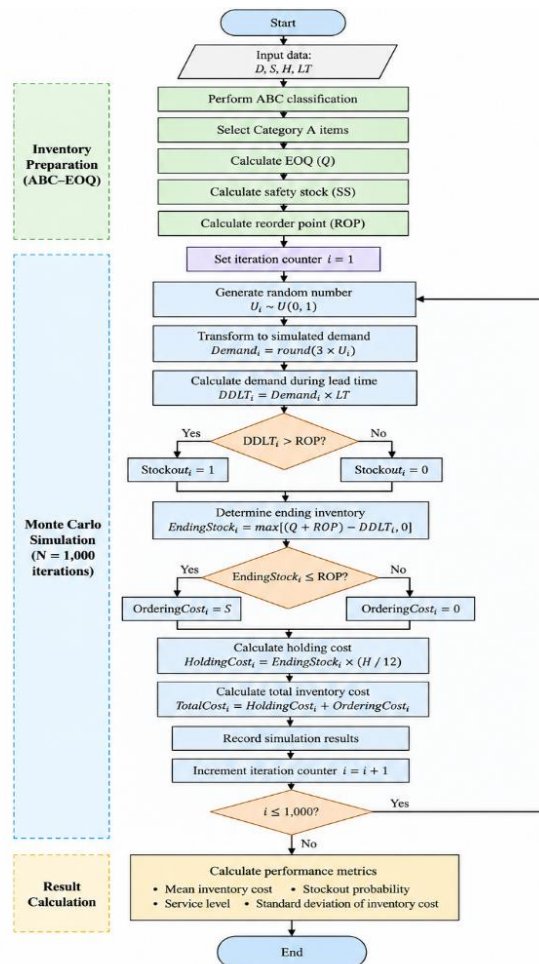


Figure 1. Research Framework of the Integrated ABC-EOQ and Monte Carlo Simulation Approach

Until the predetermined number of iterations are finished, the simulation procedure is repeated. Lastly, stockout probability, service level, mean inventory cost, and cost variability are used to assess inventory performance.

2.2 Inventory Data Collection

The required data include:

- Annual demand (D)
- Unit cost (C)
- Ordering cost (S)
- Holding cost (H)
- Lead time (LT)

Monte Carlo simulation, EOQ computation, and ABC classification all employ these parameters as inputs. Inventory analysis frequently uses ABC categorization and EOQ models to prioritize items and identify the best ordering practices.

2.3. ABC Classification

Inventory control can be performed in various ways, including using inventory value analysis. This analysis is differentiated based on the value of the investment used in a period. Typically, inventory is divided into three classes: A, B, and C; hence, the name ABC Classification. This analysis is an inventory application that uses the Pareto principle: a few critical and many trivial. The idea is to focus inventory on high-value (critical) inventory items (types) rather than low-value (trivial) ones [22].



Annual Consumption Value (ACV) is calculated as:

$$ACV_i = D_i \times C_i \quad (1)$$

Percentage Contribution:

$$Percentage_i = \frac{ACV_i}{\sum ACV_i} \times 100\% \quad (2)$$

Items are classified into:

- a) Class A: 70–80% cumulative value
- b) Class B: 15–25% cumulative value
- c) Class C: 5–10% cumulative value

Only Class A items are selected for further analysis. This approach improves inventory prioritization efficiency [23].

2.4. Economic Order Quantity (EOQ)

In the EOQ approach, the economic level is achieved by balancing ordering costs and holding costs. If inventory is large, ordering costs will decrease but holding costs will increase. Conversely, if inventory is small, ordering costs will increase but holding costs will decrease. Determining EOQ is heavily influenced by the level of demand for raw materials until the order arrives. EOQ balances ordering and holding costs. EOQ calculation can be calculated using the following formula [24][25][26]:

$$EOQ = \sqrt{\frac{2DS}{H}} \quad (3)$$

Where:

D = Annual Demand

S = Ordering Cost

H = Holding Cost

2.5. Safety Stock, Reorder Point & Total Inventory Cost

Safety stock is extra inventory held to provide insurance against fluctuations in demand. Safety stock is prepared to anticipate uncertainties in demand and supply to prevent inventory shortages. Safety stock is essential because the lead time between ordering goods and their arrival depends on the availability of goods and the distance between the buyer and supplier. Safety stock is used to mitigate uncertainty in demand [27] [28]. The formula used for safety stock is:

$$SS = Z \times \sigma_d \times \sqrt{LT} \quad (4)$$

Where:

Z = Service level factor

σ_d = Demand standard deviation

LT = Lead Time

The reorder point is the inventory level that indicates when a reorder should be placed to ensure timely delivery of the ordered goods. This ensures adequate inventory level to avoid stockout. The formula used is as follows [25] [29]:

$$ROP = (d \times LT) + SS \quad (5)$$

Total Inventory Cost (TIC) is a calculation of the total cost of raw material inventory used to prove that the optimal quantity of goods purchased, calculated using the EOQ method, will achieve minimum total inventory costs. This equation evaluates inventory cost efficiency. The formula used to calculate TIC is [25] [30]:

$$TIC = \frac{D}{Q^*} S + \frac{Q^*}{2} H \quad (6)$$

Where: Q^* = EOQ

2.6. Monte Carlo Simulation

Monte Carlo simulation was used to evaluate inventory performance under stochastic demand conditions. The simulation generates random demand values for each iteration and evaluates the resulting stockout occurrence and inventory cost based on the inventory parameters obtained from the previous analysis, including EOQ, safety stock, and reorder point. For each simulation iteration, a random number $U_i \sim$ is generated from a uniform distribution between 0 and 1:





$$U_i \sim U(0,1) \quad (7)$$

Where U_i represents the random number generated in iteration i . The random number is then transformed into discrete demand values using:

$$D_i = \text{round}(3U_i) \quad (8)$$

Where:

U_i = Random Number

D_i = Simulated Demand in iteration i

3 = Maximum observed demand level

This transformation produces fluctuating demand values that represent stochastic demand conditions.

Demand during lead time (DDLT) is calculated as:

$$DDLT = D_i \times LT \quad (9)$$

Where:

D_i = Simulated Demand

LT = Lead Time

A stockout indicator is recorded when simulated demand during lead time exceeds the reorder point, following the inventory-control criterion adopted in this study:

$$Stockout = \begin{cases} 1, & \text{if } DDLT > ROP \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

The simulation is repeated for N iterations. In this study, N is set to 1,000 iterations for each Category A item.

In addition to stockout occurrence, the simulation evaluates inventory cost for each iteration. Ending inventory is determined after considering the simulated demand, and holding cost is calculated based on the resulting ending inventory. A replenishment order is triggered when ending inventory is less than or equal to the reorder point. When a replenishment order is triggered, the fixed ordering cost S is incurred; otherwise, the ordering cost is zero. Inventory management has made extensive use of Monte Carlo simulation to assess demand uncertainty and identify the best inventory strategies. For instance, Simulation-based methods have been applied to evaluate inventory cost and service performance under stochastic demand conditions [31][32].

For each simulation iteration, the holding cost is calculated as:

$$HoldingCost_i = EndingStock_i \times \frac{H}{12} \quad (11)$$

where H is the annual holding cost per unit and the division by 12 converts the annual holding cost into a monthly equivalent.

The ordering cost is determined as:

$$OrderingCost_i = \begin{cases} S, & \text{If } EndingStock_i \leq ROP \\ 0, & \text{If } EndingStock_i > ROP \end{cases} \quad (12)$$

where S represents the fixed ordering cost per replenishment order.

The total inventory cost for each simulation iteration is then calculated as:

$$TotalCost_i = HoldingCost_i + OrderingCost_i \quad (13)$$

Stockout occurrence and replenishment triggering are treated as separate conditions in the simulation: stockout is identified when demand during lead time exceeds the reorder point, whereas replenishment is triggered when ending inventory is less than or equal to the reorder point.

2.7. Simulation Performance Metrics

Service level, mean inventory cost, and stockout likelihood are used to assess inventory performance. Under stochastic demand situations, these metrics are frequently employed in simulation-based inventory evaluation [31] [33] [34]. After completing all iterations, inventory performance metrics are calculated as follows:

Stockout Probability:

$$P_{Stockout} = \frac{\sum Stockout}{N} \quad (14)$$





$$\text{Service Level:} \quad \text{Service Level} = 1 - P_{\text{Stockout}} \quad (15)$$

$$\text{Mean Inventory Cost:} \quad \bar{C} = \frac{1}{N} \sum_{i=1}^N \text{TotalCost}_i \quad (16)$$

$$\text{Cost Variability:} \quad SD_C = \sqrt{\frac{\sum_{i=1}^N (\text{TotalCost}_i - \bar{C})^2}{N-1}} \quad (17)$$

where $N=1,000$ represents the number of simulation iterations.

2.8. Simulation Procedure

This procedure evaluates inventory performance under stochastic demand conditions by incorporating demand variability into the simulation while using the predefined lead time, EOQ, safety stock, and reorder point as inventory parameters. Monte Carlo simulation is used to generate demand scenarios and assess inventory performance under uncertainty [35]. The simulation steps are described as follows:

Step 1 Generate Random Number

Random numbers are generated using a uniform distribution between 0 and 1. For each simulation iteration i , a random value U_i is generated as follows:

$$U_i \sim U(0,1)$$

where U_i represents the random number generated in iteration i . The uniform distribution is used as the stochastic input for generating simulated demand values[36].

Step 2 Transform Random Number into Demand

The generated random number is transformed into a discrete simulated demand value using the following equation:

$$\text{Demand}_i = \text{round}(3 \times U_i)$$

where Demand_i represents the simulated demand in iteration i , and 3 represents the maximum observed demand level used in the simulation. This transformation enables the simulation to generate varying demand scenarios for evaluating inventory performance under uncertainty[35].

Step 3 Calculate Demand During Lead Time (DDLT)

Demand during lead time (DDLT) is calculated based on the simulated demand and the predefined lead time:

$$DDLT_i = \text{Demand}_i \times \text{LT}$$

Where $DDLT_i$ represents the simulated demand during lead time in iteration i , and LT represents the lead time.

Step 4 Determine Stockout Occurrence

The simulated demand during lead time is compared with the reorder point. A stockout indicator is recorded when DDLT exceeds ROP. A stockout is recorded when demand during lead time exceeds the reorder point[37].

$$\text{Stockout}_i = \begin{cases} 1, & \text{if } DDLT_i > ROP \\ 0, & \text{if } DDLT_i \leq ROP \end{cases}$$

Where Stockout_i represents the stockout indicator in iteration i and ROP represents the reorder point

Step 5 Determine Ending Inventory

For each simulation iteration, the ending inventory is determined based on the available inventory and the simulated demand during lead time. The resulting ending inventory is subsequently used to determine the holding cost and replenishment condition.

$$\text{EndingStock}_i = \max[(Q + ROP) - DDLT_i, 0]$$

Where EndingStock_i represents ending inventory in iteration i , Q represents the EOQ, ROP represents the reorder point, $DDLT_i$ represents demand during lead time in iteration i

Step 6 Calculate Inventory Cost

Simulation-based inventory models can be used to evaluate inventory cost and service performance under demand uncertainty [38]. For each simulation iteration, holding cost is calculated based on the resulting ending inventory:





$$HoldingCost_i = EndingStock_i \times \frac{H}{12}$$

Determine ordering cost based on the replenishment condition:

$$Ordering\ Cost_i = \begin{cases} S, & \text{If } EndingStock_i \leq ROP \\ 0, & \text{If } EndingStock_i > ROP \end{cases}$$

Calculate total inventory cost:

$$TotalCost_i = HoldingCost_i + OrderingCost_i$$

These calculations allow inventory cost to be evaluated for each simulated demand scenario.

Step 7 Repeat the Simulation

Steps 1 to 6 are repeated for N=1,000 iterations for each Category A item. The results of each iteration, including stockout occurrence, ending inventory, holding cost, ordering cost, and total inventory cost, are recorded for subsequent analysis. Repeated simulation enables the estimation of inventory performance measures under stochastic demand conditions [35].

Step 8 Calculate Performance Metrics

After completing all simulation iterations, the simulation results are used to calculate stockout probability, service level, mean inventory cost, and cost variability. These performance measures are used to evaluate inventory behavior under the simulated demand scenarios[38]. The mathematical formulations of these performance measures are presented in Section 2.7.

The Monte Carlo simulation procedure used in this study is summarized in figure 2.

Input:

Annual demand (D)
Ordering cost (S)
Holding cost per unit (H)
Lead time (LT)
Order quantity (Q)
Safety stock (SS)
Reorder point (ROP)
Number of simulations (N = 1,000)

Step 1: Perform ABC classification.

Step 2: Select Category A items.

Step 3: Calculate Economic Order Quantity (EOQ).

Step 4: Calculate safety stock (SS).

Step 5: Calculate reorder point (ROP).

Step 6: Set iteration counter i = 1.

Step 7: Generate random number $U_i \sim U(0,1)$.

Generate simulated demand:

Demand_i = round($3 \times U_i$)

Calculate demand during lead time:

DDLT_i = Demand_i × LT

Determine stockout occurrence:

If DDLT_i > ROP:

Stockout_i = 1

Else:

Stockout_i = 0

Determine ending inventory:

EndingStock_i = max[(Q + ROP) – DDLT_i, 0]



Calculate holding cost:
 $\text{HoldingCost}_i = \text{EndingStock}_i \times (H/12)$
Determine ordering cost:
If $\text{EndingStock}_i \leq \text{ROP}$:
 $\text{OrderingCost}_i = S$
Else:
 $\text{OrderingCost}_i = 0$
Calculate total inventory cost:
 $\text{TotalCost}_i = \text{HoldingCost}_i + \text{OrderingCost}_i$

Record the simulation results.

Step 8: Set $i = i + 1$.

If $i \leq N$:

 Return to Step 7.

Otherwise:

 Proceed to Step 9.

Step 9: Calculate performance metrics:

 Mean inventory cost

 Stockout probability

 Service level

 Standard deviation of inventory cost

Output:

Inventory performance metrics for each Category A item.

Figure 2. Monte Carlo Inventory Simulation Procedure

This algorithm allows the evaluation of inventory policies by incorporating demand variability while using predefined lead time and inventory control parameters. The simulation provides estimates of stockout probability, service level, mean inventory cost, and cost variability for Category A spare parts under the simulated demand scenarios. Monte Carlo simulation has been widely used to assess service level, stockout probability, and cost performance in stochastic inventory systems. Therefore, the proposed simulation framework provides estimates of inventory performance under the simulated demand conditions.

3. RESULT AND DISCUSSION

3.1. ABC Classification Results

Based on yearly consumption value, which is computed as the product of annual demand and unit cost, ABC classification is used to identify priority inventory items. The Pareto principle is then used to rank the items in descending order and divide them into three classes (A, B, and C). According to the classification results, 32 of the 125 inventory items are categorized as Category A, representing 25.6% of the total items and accounting for approximately 80% of the total inventory value. Category B consists of 38 items, representing 30.4% of the total items and contributing approximately 15% of the total inventory value. Category C consists of 55 items, representing 44.0% of the total items and contributing approximately 5% of the total inventory value. Category A items are selected for further analysis using EOQ and Monte Carlo simulation.

Table 2. ABC Classification Summary

Category	Item Range	Number of Items	Percentage of Items	Cumulative Value
A	1-32	32	25.6%	80%
B	33-89	38	30.4%	95%
C	90-125	55	44.0%	100%

Table 2 illustrates that Category A comprises 32 items, representing 25.6% of the total inventory items and accounting for approximately 80% of the total inventory value. Category B comprises 38 items, representing 30.4% of the total inventory items and contributing approximately 15% of the total inventory value. Category C comprises 55 items, representing 44.0% of the total inventory items and contributing approximately 5% of the total inventory value.

A Pareto chart is used to display the ABC categorization findings in order to prioritize inventory items according to their contribution to the total inventory value. The Pareto principle is used in the graphic to divide inventory items into three groups. Items in category A have the greatest contribution, those in category B have a moderate impact, and those in category C have a relatively modest contribution. Because Category C items represent a high number of products with little effect on the total inventory value, they are combined into a single bar to increase visualization clarity.

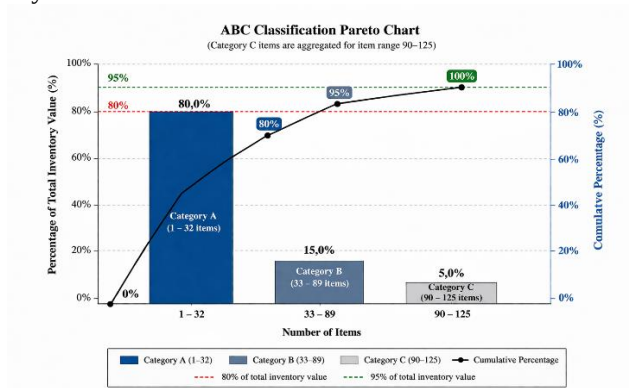


Figure 3. Pareto Chart of ABC Classification Showing Cumulative Inventory value.

The products in category A, which make up around 80% of the overall inventory value, are ranked from 1 to 32, as seen in Figure 3. Strict inventory control is necessary for these items since they are regarded as essential. Items in Category B, which range in ranking from 33 to 89, account for around 15% of the overall inventory value and call for moderate control. In contrast, only roughly 5% of the overall inventory value is contributed by category C, which is made up of items ranked between 90 and 125.

Table 3 displays the Category A objects that were found using the ABC classification. These products are ranked according to their yearly consumption value, which is determined by multiplying the unit cost by the annual demand. The most important spare parts that have a major impact on the overall inventory investment are displayed in the table. For additional analysis utilizing EOQ and Monte Carlo simulation, only category A items are taken into account.

Table 3. Category A Inventory Items Based on ABC Classification and Annual Consumption Value

N o	Item Description	Annual Demand (Unit)	Unit Cost	Annual Consumpti on Value (Rp)	Annual Consum ption Value Percenta ge (%)	Cumulati ve (%)	Categ ory
1	SHEET PACKING AR 8550 5mm ARTECH	12	Rp 9,078,643	Rp 108,943,711	13.88%	13.88%	A
2	SPHERICAL ROLLER THRUST BEARING 29420 E1	17	Rp 4,060,000	Rp 69,020,000	8.79%	22.67%	
3	SHAFT 125 X 4133	2	Rp 20,316,400	Rp 40,632,799	5.18%	27.85%	



4	SPHERICAL ROLLER BEARING 22226 E1	17	Rp 2,210,000	Rp 37,570,000	4.79%	32.64%
5	THYSSEN 1730 SPUR GEAR C/W HARDENED 264 X 211 FOR SCREW PRESS KUY P15	5	Rp 5,600,000	Rp 28,000,000	3.57%	36.21%
6	SPHERICAL ROLLER BEARING 22220 E1	17	Rp 1,290,000	Rp 21,930,000	2.79%	39.00%
7	MECHANICAL SEAL AR-820/NST-V ID35	19	Rp 1,150,000	Rp 21,850,000	2.78%	41.78%
8	SPHERICAL ROLLER THRUST BEARING FAG 29417 E	5	Rp 4,258,017	Rp 21,290,083	2.71%	44.50%
9	FLANGE UNIT BEARING UCF 315	15	Rp 1,395,429	Rp 20,931,429	2.67%	47.16%
10	MECHANICAL SEAL TIFFANY TF PB09/L02 38mm	9	Rp 2,300,000	Rp 20,700,000	2.64%	49.80%
:	:	:	:	:	:	:
32	SPIRAL WOUND GASKET CLASS 600 6"	12	Rp 495,853	Rp 5,950,235	0.76%	80%

The first 32 products make up about 80% of the overall inventory value, as Table 3 illustrates. Sheet Packing AR 8550 5mm ARTECH has the largest contribution at 13.88% of the total inventory value, followed by Spherical Roller Thrust Bearing 29420 E1 at 8.79% and Shaft 125 x 4133 at 5.18%. These findings show that the entire inventory investment is dominated by a very small number of spare parts. The majority of category A goods are made up of vital mechanical parts like gears, bearings, and seals that are necessary to keep the palm oil processing plant running. In order to identify the best ordering strategies under stochastic demand conditions, these items are chosen for additional investigation utilizing EOQ optimization and Monte Carlo simulation.

3.2. EOQ Calculation Results

EOQ calculations are only carried out for category A items after the ABC classification. Stricter inventory control is necessary since these items have the largest inventory investment. The best order quantity that reduces overall inventory costs is found using the EOQ model. To guarantee inventory availability throughout lead time, safety stock and reorder point are also computed. Table 4 displays the results of the EOQ calculation for category A products.

Table 4. EOQ, Safety Stock, and Reorder Point for Category A Spare Parts

No	Item Description	EOQ (Q)	Safety Stock (SS)	Reorder Point (ROP)
1	Spherical Roller Thrust Bearing 29420 E1	10	1	2
2	Sheet Packing AR 8550 5 mm Artech	5	1	2
3	Shaft 125 x 4133	1	1	1
4	Spherical Roller Bearing 22226 E1	13	1	2
5	Thyssen Spur Gear	4	1	1
6	Spherical Roller Bearing 22220 E1	17	1	2
7	Mechanical Seal AR-820/NST-V ID35	19	2	2
8	Spherical Roller Thrust Bearing FAG 29417 E	5	1	1
9	Flange Unit Bearing UCF 315	15	2	2
10	Mechanical Seal Tiffany TF PB09/L02	13	2	2
11	Packing Pintu Sterilizer ARTECH 10mm	236	9	11
:	:	:	:	:



29	Ball Bearing 6307 ZZ/C3	144	5	5
30	Spiral Wound Gasket Class 150 6"	28	1	2
31	Mechanical Seal AR-820/NWT-V ID38	9	1	1
32	Spiral Wound Gasket Class 600 6"	23	2	1

A summary of the EOQ, safety stock, and reorder point values for category A goods is provided to give an overview of the outcomes of the EOQ calculation. This synopsis emphasizes how inventory control parameters vary among essential spare components. Table 5 displays the EOQ summary results.

Table 5. Summary of EOQ Results for Category A Items

Parameter	Minimum	Maximum	Average
EOQ (Q)	1	236	32.47
Safety Stock (SS)	1	9	2.16
Reorder Point (ROP)	1	11	2.94

The EOQ values for category A items vary significantly, as Table 5 illustrates. Packing Pintu Sterilizer Merk Artech 10 mm has the highest EOQ value of 236 units among the Category A items. In contrast, several items, such as Shaft 125 x 4133 and Spherical Roller Bearing SKF 23034 CC/W 33, have EOQ values close to one unit. The safety stock values range from 1 to 9 units, while the reorder point values range from 1 to 11 units. These results indicate that the inventory control parameters vary across spare parts according to their demand and cost characteristics.

To compare the effectiveness of the EOQ policy with the existing inventory practice, total inventory cost is calculated using both approaches. The existing policy assumes that items are ordered based on annual demand without optimization, while the EOQ policy determines optimal order quantity. The comparison of total inventory cost is presented in Table 6.

Table 6. Total Inventory Cost Comparison Between Existing Policy and EOQ

No	Item Description	TIC Existing (Rp)	TIC EOQ (Rp)	Saving (Rp)	Saving (%)
1	Sheet Packing AR 8550	6,491,743	5,182,620	1,309,123	20.16%
2	Spherical Roller Thrust Bearing	5,608,233	4,282,533	1,325,700	23.64%
3	Shaft 125 x 4133	4,843,804	3,785,708	1,058,096	21.84%
4	Spherical Roller Bearing	4,662,100	3,314,310	1,347,790	28.91%
5	Thyssen Spur Gear	3,832,000	3,094,000	738,000	19.26%
:	:	:	:	:	:
29	Ball Bearing 6307	2,186,552	1,597,112	589,440	26.95%
30	Spiral Wound Gasket 150	2,642,890	2,176,412	466,478	17.65%
31	Mechanical Seal AR-820	2,541,350	2,121,350	420,000	16.52%
32	Spiral Wound Gasket 600	2,714,128	2,304,128	410,000	15.10%

3.3. Monte Carlo Simulation Results

Monte Carlo simulation is performed to evaluate inventory performance under stochastic demand conditions. The EOQ parameters obtained from the previous analysis, including order quantity, safety stock, and reorder point, are used as inputs in the simulation. Random demand values are generated using uniform distribution and simulated over 1,000 iterations for each category A item. The simulation evaluates stockout probability, service level, mean inventory cost, and cost variability. The results of Monte Carlo simulation are presented in Table 7.

Table 7. Monte Carlo Simulation Results for Category A Items

Product ID	Mean Cost (Rp)	Stockout Probability	Service Level	Std Dev Cost
1	538,189	0.183	0.817	80,208
2	577,714	0.151	0.849	35,060
3	1,070,544	0.144	0.856	465,100
4	313,659	0.162	0.838	19,194
5	717,143	0.181	0.819	566,043
6	230,883	0.144	0.856	10,974
7	237,229	0.000	1.000	10,022

8	487,234	0.182	0.818	38,277
9	107,895	0.000	1.000	12,160
10	305,371	0.000	1.000	19,662
...	...	...	...	...
32	38,817	0.000	1.000	4,225

The simulation results show that the service level values for Category A items range from 0.811 to 1.000, corresponding to stockout probabilities ranging from 0.000 to 0.189. Several items achieve a service level of 1.000, indicating that no stockout events were recorded during the 1,000 simulation iterations for those items. Other items show service level values below 1.000, reflecting the occurrence of stockout events under the simulated demand scenarios. These results demonstrate differences in inventory performance across Category A items under stochastic demand conditions.

To assess inventory performance under stochastic demand conditions, the service level derived from Monte Carlo simulation is examined. The likelihood that inventories will be adequate to satisfy demand during lead time is represented by the service level. Figure 3 shows the distribution of service level values for category A items.

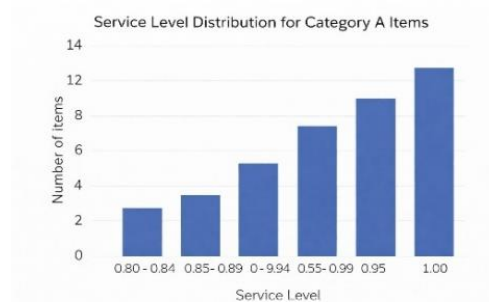


Figure 3. Service Level Distribution for Category A Items based on Monte Carlo Simulation

Figure 3 shows the distribution of service level values for Category A items. Most items exhibit service level values above 0.80, while several items achieve a service level of 1.000. The variation in service level values indicates differences in the occurrence of stockout events across the simulated demand scenarios.

Stockout probability represents the proportion of simulation iterations in which the stockout condition was recorded. As shown in Figure 4, most Category A items have stockout probability values below 0.20, while several items have a stockout probability of 0.000. The variation in stockout probability reflects differences in simulated demand conditions and the inventory parameters applied to each item.

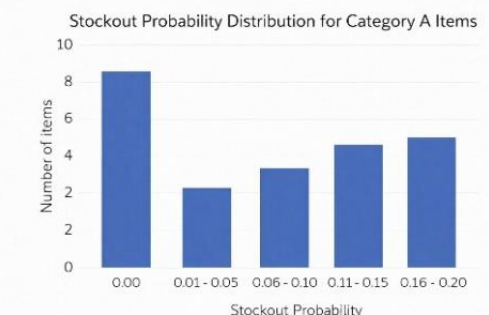


Figure 4. Stockout Probability Distribution for Category A items

Monte Carlo simulation also provides information on inventory cost variability under stochastic demand conditions. Mean inventory cost and standard deviation are calculated across the 1,000 simulation iterations for each Category A item. Figure 5 illustrates the variation in inventory cost among the items. Differences in mean cost and cost variability are associated with differences in demand, unit cost, holding cost, and inventory control parameters. Compared with deterministic EOQ analysis, the simulation provides additional information on the distribution and variability of inventory cost under the simulated demand scenarios.

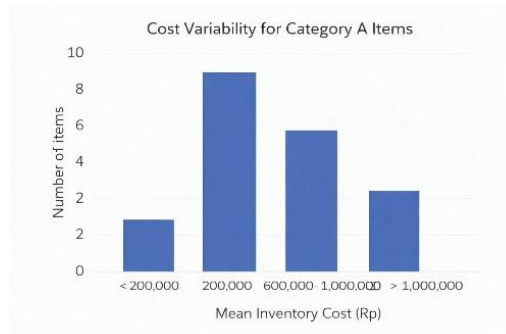


Figure 5. Distribution of Mean Inventory Cost for Category A Items

Figure 5 presents the distribution of mean inventory cost across Category A items. Differences in mean cost are associated with variations in demand, unit cost, holding cost, and inventory control parameters. The integrated ABC classification, EOQ model, and Monte Carlo simulation provide a comprehensive evaluation of inventory performance under stochastic demand conditions. The ABC analysis identified 32 category A items that contribute significantly to the total inventory value, indicating that these items require stricter inventory control. The classification identifies Category A items as the subset selected for further inventory analysis.

The optimal order quantities for each item vary according to the findings of the EOQ calculation, which reflects variations in demand levels, holding costs, and ordering costs. EOQ values are typically greater for items with higher yearly demand and lower for items with lower demand. Additional defense against demand fluctuations during lead time is offered by the safety stock and reorder point computations. Stochastic demand is included into Monte Carlo simulation to further assess inventory performance. According to the simulation results, service level values between 0.811 and 1.000 correspond to stockout probabilities between 0 and 0.189. The results show that service level values vary from 0.811 to 1.000 across the simulated Category A items. During simulated runs, a number of items reach a service level of 1.000, indicating that there are no stockouts. These results indicate variation in service level and inventory cost across the evaluated items under the simulated demand scenarios.

The cost variability analysis shows that mean inventory cost differs across items due to differences in demand patterns and holding costs. Items with higher variability exhibit larger standard deviation values, indicating greater uncertainty in inventory performance. Compared to deterministic EOQ analysis, Monte Carlo simulation provides additional insight into risk and uncertainty, allowing better evaluation of inventory policies. Overall, the combination of Monte Carlo simulation, EOQ optimization, and ABC classification enhances inventory management decision-making. Businesses can use this method to assess performance under stochastic demand conditions, identify priority goods, and calculate the best order numbers.

4. CONCLUSION

This study developed and evaluated an integrated inventory management approach combining ABC classification, Economic Order Quantity (EOQ), safety stock, reorder point, and Monte Carlo simulation for spare parts inventory in a palm oil processing plant. The ABC classification identified 32 Category A items, representing 25.6% of the total 125 inventory items and accounting for approximately 80% of the total inventory value. These items were subsequently selected for EOQ, safety stock, reorder point, and Monte Carlo analysis. The EOQ analysis produced different order quantities, safety stock levels, and reorder points across the Category A items. The EOQ-based total inventory cost was lower than the existing inventory policy by approximately 15% to 29%, with an average saving of approximately 22% across the evaluated Category A items. These results indicate differences in inventory cost between the existing ordering practice and the EOQ-based policy. The Monte Carlo simulation, conducted over 1,000 iterations for each Category A item, generated service level values ranging from 0.811 to 1.000 and stockout probabilities ranging from 0.000 to 0.189. The average service level across Category A items was approximately 0.88. The mean inventory cost obtained from the simulation ranged from approximately Rp 7,764 to Rp 1,281,248, while the standard deviation of cost varied across items. Overall, the integration of ABC classification, EOQ, and Monte Carlo simulation provides a framework for evaluating spare parts inventory performance by combining item prioritization, order quantity determination, and stochastic demand-based performance assessment. The framework enables inventory cost, stockout probability, service level, and cost variability to be evaluated simultaneously for Category A spare parts.



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