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Inventory optimization model using Artificial Neural Network method and Continuous Review (s,Q)

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Abstract
The medical device industry company experienced the problem of prolonged accumulation of finished goods in the warehouse, causing one of the safety box items to be defective and damaged. Therefore, this study aims to plan demand forecasting and design inventory policies that consider repair items caused during the buildup of finished goods in the warehouse to minimize total inventory costs using ANN and Continuous Review (s,Q) methods. Demand forecasting is carried out for the next 20 months, from May 2023 to December 2024, using the ANN model with a total forecasting of 17936 units of inner items and 3370 units of outer items. After that, the inventory policy calculation uses the continuous review (s,Q) method. The calculation results show a decrease in the total inventory cost on inner items by 83% and outer items by 79%. After demand forecasting, there was also a decrease in the total initial inventory cost of inner items by 81% and outer items by 80%. This research develops an inventory optimization model that considers repair items due to the accumulation of goods in the warehouse by integrating holding cost, ordering cost, and repair cost variables to develop inventory policies to be more effective and efficient and to utilize damaged products for repair and resale. The limitation of this research is that it only gets demand forecasting results for the next 20 months because the company only started operating in September 2021 and limited data access. It is hoped that future researchers can plan and design an inventory policy strategy with demand forecasting for the next 10 years, focusing on repair items caused by the accumulation of finished goods in the warehouse.

Keywords:
ANN;
Continuous review (s,Q);
EOQ;
Overstock;

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INTRODUCTION

The medical device industry cannot be separated from the care industry, so improving supply chain efficiency in the medical device industry is necessary to improve services in the healthcare industry [1]. This research focuses on the medical device industry, specifically a safety box assembly company. Under its management, the company experienced a buildup of finished goods in the warehouse due to the COVID-19 pandemic that occurred previously.

Several industries have experienced production and logistics disruptions due to global supply chain instability caused by the pandemic [2]. During the COVID-19 pandemic, the consumption of medical devices increased sharply [3][4]. However, in 2023, the COVID-19 pandemic began to decline, and the spread of vaccinations was widespread, so the consumption of medical devices began to stabilize again.

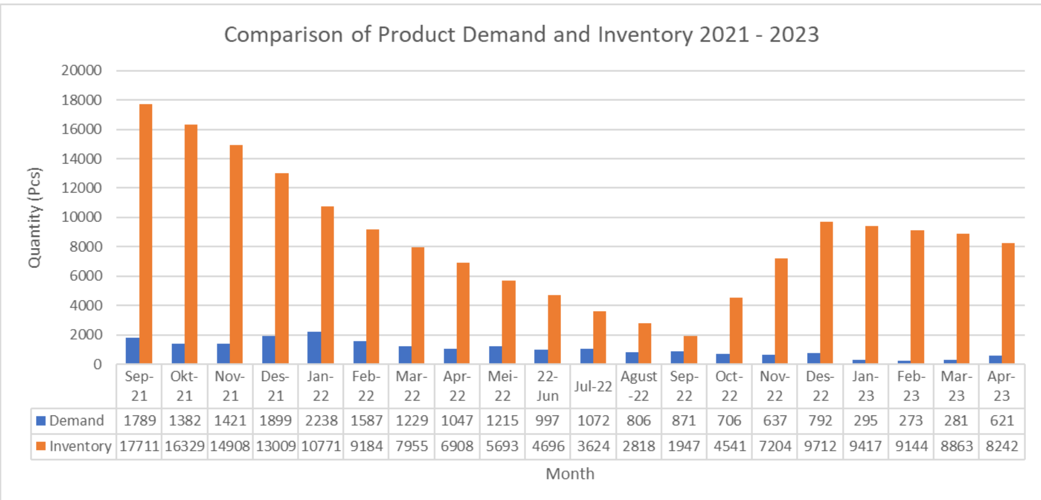
The problem is that safety box products produced to support the logistics of medical devices in health facilities accumulate in the warehouse because the demand for safety boxes has dropped significantly. Therefore, the supply and demand in this company experienced the gap shown in Figure 1.

Based on Figure 1, a gap occurs due to higher inventory than demand. The accumulation of finished goods in the warehouse is due to the company continuing to carry out the production process, where the number of reorder lots is the number of previous orders lots caused by the accumulation of finished goods in the warehouse. Reordering is carried out continuously because the company needs a standard inventory policy, and the company must ensure that there are no shortages or lost sales. Since the relevant cost is affected by the present value of time and some products deteriorate over time, it can be seen that the gap that occurs is caused by high inventory compared to demand [1].

Several damaged products caused the company losses, which totaled IDR 13,635,000.00. The total cost of losses is one component of the total inventory cost that needs to be considered in inventory control. The accumulation of goods causes this loss cost, so the product becomes damaged or shrinks. The company prefers to repair products rather than make new products because processing new products is more expensive than repairing repair costs [2]. Items that can be or are repaired are becoming an increasing trend to invest in [3].

According to [8][9], the core operational component of supply chain control provides accurate, complete, and timely information for when to order or issue and maintaining acceptable stock levels of all products to reduce shortages and excess stock. Therefore, inventory needs to be managed in such a way as to avoid the possibility of lost sales or excessive costs due to inventory buildup [10, 11, 12, 13, 14]. There are several studies that have been done to minimize the total cost of inventory [15, 16, 17, 18, 19, 20]. By implementing a continuous review inventory system, monitoring will be carried out continuously and in real-time inventory levels and demand. Companies can maintain inventory levels that match actual needs, avoid overstock, and reduce overall inventory costs.

Based on the previously described problems, the solution is to plan demand forecasting and design a continuous review inventory system to reduce total inventory costs. In this study, the contribution is to integrate and add variables of holding cost, ordering cost, and repair cost caused by the accumulation of finished goods in the warehouse, where the objective function is to reduce the total inventory cost. Planning demand forecasting and designing inventory policies that consider repair items caused during the buildup of finished goods in the warehouse is an essential step for industrial management to develop inventory policies to be more effective and efficient in accounting for and utilizing damaged products for repair and resale. It can also help companies minimize total inventory costs and increase profits. In addition, research has yet to focus on designing inventory policies that consider repair items caused by the accumulation of finished goods in the warehouse. Therefore, this research is expected to help companies and other researchers who focus on considering repair items caused by the accumulation of finished goods in the warehouse.



	Sep-21	Okt-21	Nov-21	Des-21	Jan-22	Feb-22	Mar-22	Apr-22	Mei-22	22-Jun	Jul-22	Agust-22	Sep-22	Oct-22	Nov-22	Des-22	Jan-23	Feb-23	Mar-23	Apr-23
Demand	1789	1382	1421	1899	2238	1587	1229	1047	1215	997	1072	806	871	706	637	792	295	273	281	621
Inventory	17711	16329	14908	13009	10771	9184	7955	6908	5693	4696	3624	2818	1947	4541	7204	9712	9417	9144	8863	8242

Figure 1. Comparison of Product Demand and Inventory 2021-2023

METHOD

Material

PT BEM Industry produces a sharp medical waste container, often called a Safety Box. The safety box has two parts: inner and outer. However, the repair focuses only on the outer part because it is made of aluminum, which causes it to deform easily. In addition, the inner part is inserted into the outer part to protect the inner part.

Methods

The study used a quantitative approach, where inventory planning and design were carried out due to the accumulation of finished goods in the warehouse to minimize the total inventory cost at the PT BEM Industry. The method used is included in optimization research using the ANN method to plan demand forecasting and the Continuous Review method, which is a continuous review policy to design policies to optimize inventory by minimizing total inventory costs [21, 22, 23, 24, 25]. The ANN method is a popular method with fast and reliable computational techniques that produce accurate forecasts [26, 27, 28, 29, 30, 31].

According to [32][33], the ANN method can provide accurate results and a smaller MAPE value than the ARIMA method. In addition, the principle of Continuous Review (s,Q) is that inventory must be continuously monitored and checked periodically to ensure that the availability of products and raw materials is sufficient with no excess or shortage of inventory. In repairable items, a control tower is needed that has two different functions, namely generating warnings for future stockouts and making decisions to accelerate product repair [4]. The Continuous Review (s,Q) method was selected because the assumptions must be met in accordance with company conditions such as customarily distributed demand data, constant order lot size (q0), and constant lead time in accordance with this study.

Research Stages

Stages 1

The first stage of this research is data collection, which is used to forecast demand for the following 20 periods (May 2023 - December 2024) using ANN. Before demand forecasting, regular distribution testing is carried out using the Kolmogorov-Smirnov test on the demand data for each item to qualify the Continuous Review (s,Q) method. Testing is carried out before forecasting to facilitate the calculation. In demand forecasting, input data is required to be processed as output or demand forecasting results. The ANN model used is multilayer perception with a backpropagation algorithm. Several parameters must be determined to adjust the conditions in this study, as described in Table 1 based on several references [31, 32, 33]. After that, it will be processed using the ANN method with MATLAB software tools to display the network and processing results.

Stages 2

Calculating the inventory policy is the price data for each product item in 2023, demand data from the period Sept 2021 - April 2023, constant lead time, which is 2 weeks after ordering, standard deviation, cost data used are ordering costs, storage costs, shortage costs, and repair costs as shown in Figure 2. This data is obtained from the source responsible for inventory at the PT BEM Industry warehouse, and the assumptions used in the calculation are as follows.

D : Total product demand (Units)
S : Standard Deviation Product demand (Unit)
m : Remaining inventory
h : Holding cost (Rp/unit)
A : Ordering Cost (Rp/unit)
C : Unit price of product items (Rp/unit)
f : Ordering Frequency
Cu : Product shortage cost (Rp/unit)
L : Leadtime
P : Repairing Cost (Rp/unit)
Q_p : Number of improvements per unit product item (unit)
O_A : Total Ordering Cost (Rp/unit)
O_h : Total Holding Cost (Rp/unit)
O_{Cu} : Total Shortage Cost (Rp/unit)
O_p : Total Repairing Cost *outer* item(Rp/unit)
O_T : Total Cost Inventory (Rp/unit)

Table 1. ANN Model Parameters

No	Parameters	Parameter Selection
1	Training Function	Traingd
2	Adaption Learning Function	Learngd
3	Performance Function	MSE
4	Transfer Function	Tansig
5	Epoch	Max 3000

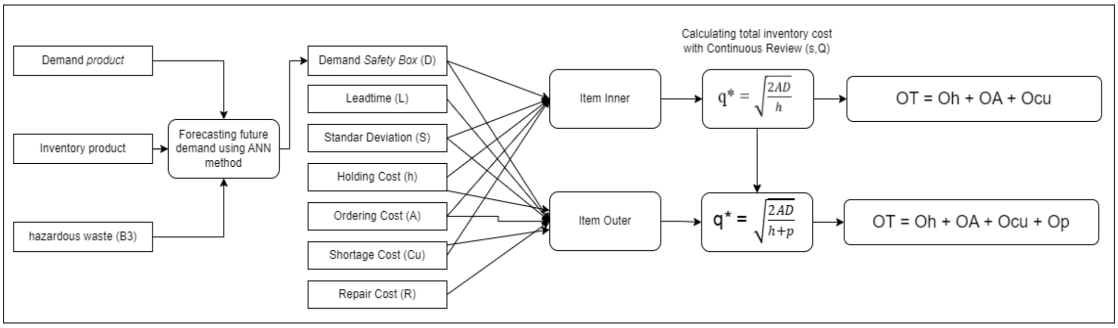


Figure 2. Process Stages

After that, the collected data is used to calculate the optimal order quantity with the Q item repair model according to the Wilson model and Continuous Review (s,Q) according to the Wilson model [18][35].

i. The repair items must be considered when calculating the optimal order quantity [5]. This is assumed because the damage to the product may be different and require different repair costs. Therefore, the equation becomes as follows for calculating the optimal order quantity (q_0).

$$qo_1^* = \sqrt{\frac{2AD}{(h+p)}} \quad (1)$$

ii. Based on the qo_1^* obtained, it can determine the magnitude of the possible inventory shortage (α). Then, the reorder point can be calculated using the following Continuous Review (s,Q) equation.

$$\alpha = \frac{hqo1*}{CuD+hqo1*} \quad (2)$$

$$r_1^* = DL + Z\alpha\, S\sqrt{L} \quad (3)$$

From the α value, the Zα value will be obtained with the equation $Z_{(1-\alpha)}$, which can be found using the normal distribution table.

iii. After the value of r1 has been obtained, we can find the value of qo_2, which can be calculated using the following equation.

$$qo_2^* = \sqrt{\frac{2D[A+Cu\int_{r1}^{\infty}(x-r1)(fx)dx}{(h+p)}} \quad (4)$$

Where,

$$\int_{r1}^{\infty}(x-r1)(fx)dx - SL[f(Z\alpha) - Z\alpha\, \psi(Z\alpha)] = N \quad (5)$$

The values of f(Zα) and ψ(Zα) are found using the partial expectation table, so the equation follows.

$$N = SL[f(Z\alpha) - Z\alpha\, \psi(Z\alpha)] \quad (6)$$

iv. Then, recalculate the values of α and r_2 using the following equation.

$$\alpha = \frac{hqo2*}{CuD+hqo2*} \quad (7)$$

$$r_2^* = DL + Z\alpha\, S\sqrt{L} \quad (8)$$

After getting the result r_2, compare it with r_1. If the value of r_1 is relatively the same as r_2, then the iteration is complete, and $r_1^*=r_2^*$ and $qo_1^*=qo_2^*$will be obtained. If the values of r_1 and r_2 are not the same, then return to stage iii by changing the $r_1^*=r_2^*$ and $qo_1^*=qo_2^*$.

After obtaining the optimal ordering value q_0 *, the maximum inventory level, safety stock, service level, and total inventory cost can be calculated to minimize the total inventory cost using the following equation from Figure 2.

$$O_T = O_A + O_h + O_{cu} + O_p \quad (9)$$

There is a limitation for cost, which considers repair costs only focusing on outer items because the products that receive the heaviest load and are easily deformed are outer items. Continuous review (s,Q) is performed based on the calculated total inventory cost to reduce the total inventory cost. The proposed total inventory cost results will be compared with the existing total inventory cost condition and the total inventory cost condition before demand forecasting to validate the model with the objective function of minimizing the total inventory cost.

RESULTS AND DISCUSSION

Results of demand forecasting using ANN

Safety box product demand data from September 2021 - April 2023 was tested for normal distribution using the Kolmogorov Smirnov Test with the IBM SPSS tool with the following hypothesis.

Hypothesis

H0 : Raw material demand data is normally distributed

H1 : Raw material demand data is not normally distributed

Decision Making:

If Sig.(p) > 0,05 then H0 is not rejected (accepted)

If Sig.(p) <= 0,05 then H0 is rejected

One-Sample Kolmogorov-Smirnov Test

		Permintaan_Inner
N		20
Normal Parameters[a,b]	Mean	888.4000
	Std. Deviation	484.41722
Most Extreme Differences	Absolute	.086
	Positive	.086
	Negative	-.076
Test Statistic		.086
Asymp. Sig. (2-tailed)		.200[c,d]

a. Test distribution is Normal.

b. Calculated from data.

c. Lilliefors Significance Correction.

d. This is a lower bound of the true significance.

Figure 3. Kolmogorov Smirnov Test Outer Item

One-Sample Kolmogorov-Smirnov Test

		Permintaan_Outer
N		20
Normal Parameters[a,b]	Mean	169.5000
	Std. Deviation	70.73040
Most Extreme Differences	Absolute	.153
	Positive	.153
	Negative	-.118
Test Statistic		.153
Asymp. Sig. (2-tailed)		.200[c,d]

a. Test distribution is Normal.

b. Calculated from data.

c. Lilliefors Significance Correction.

d. This is a lower bound of the true significance.

Figure 4. Kolmogorov Smirnov Test Inner Item

Based on Figure 3 and Figure 4 with the distribution test on raw material demand data on inner items and outer items using the Kolmogorov-Smirnov test, the Asymp. Sign (2-tailed) > 0.05, then H0 is not rejected. So, the actual product demand data is typically distributed and meets the Continuous Review (s,Q) policy requirements.

In forecasting demand using the ANN method, the first step is data classification by grouping data into input and output data. In the input data, demand and inventory data were taken from September 2021 to April 2023, but the company was established during the COVID-19 pandemic, so the data is considered less relevant. Therefore, additional data is needed, such as B3 waste data for January 2018- December 2019, a safety box demand converted into product capacity to be used as a safety box product requirement for B3 waste. In addition, B3 waste data can assist companies in providing an overview of demand patterns before the COVID-19 pandemic.

After that, data normalization and data processing are carried out to forecast demand using the ANN method with MATLAB tools to obtain demand forecasting results for the following 20 periods, from May 2023 to December 2024.

From Table 3, data normalization is performed to facilitate faster calculations ranging from 0 to 1 and reduce data redundancy. After that, the data processing process is carried out to obtain the results of demand forecasting from May 2023 to December 2024 using the ANN method that has been adjusted to the conditions of the predetermined parameters. The results are shown in Table 4. After that, a denormalization calculation is carried out to restore the value of the demand forecasting results to the original unit and eliminate redundant data, as described in Table 5. Table 6 explains the comparison of the existing conditions of actual demand and the results of demand forecasting using the ANN method; it is found that the total demand for inner items has increased from 17768 units to 17936 units, and for outer items has also increased from 3370 units to 3390 units.

Table 2. Input dan Output ANN

Neuron		Description
X1 *(Inner Item Layer Input)*	X1	Historical Demand Data of Inner Items from September 2021-April 2023
	X2	Actual Inventory Data of Inner Item Finished Goods
	X3	Hazardous Waste Data for 2018-2019
X2 *(Outer Item Layer Input)*	X1	Historical Demand Data of Outer Items from September 2021-April 2023
	X2	Actual Inventory Data of Outer Item Finished Goods
	X3	Hazardous Waste Data for 2018-2019
y' *(Output)*	y1'	Forecasting Demand for Inner Goods for the next 20 months (from Mei 2023-December 2024)
	y2'	Forecasting Demand for Outer Goods for the next 20 months (from Mei 2023-December 2024)

Table 3. Normalization Data

Year	Month	Inner Item			Outer Item		
		X1	X2	X3	X1	X2	X3
2021	September	0.697	0.900	0.10	0.885	0.900	0.10
	October	0.520	0.834	0.10	0.815	0.807	0.10
	November	0.555	0.763	0.10	0.670	0.727	0.10
	December	0.752	0.666	0.10	0.844	0.632	0.10
2022	January	0.900	0.551	0.10	0.900	0.531	0.10
	February	0.634	0.470	0.10	0.644	0.453	0.10
	March	0.501	0.406	0.10	0.396	0.400	0.10
	April	0.428	0.352	0.10	0.319	0.353	0.10
	May	0.519	0.285	0.10	0.204	0.317	0.10
	June	0.379	0.238	0.10	0.533	0.251	0.10
	July	0.426	0.184	0.10	0.430	0.194	0.10
	August	0.309	0.145	0.10	0.389	0.141	0.10
	September	0.355	0.100	0.9	0.256	0.100	0.9
	October	0.256	0.246	0.9	0.448	0.145	0.9
	November	0.235	0.396	0.9	0.363	0.199	0.9
	December	0.309	0.535	0.9	0.337	0.255	0.9
2023	January	0.109	0.522	0.9	0.119	0.227	0.9
	February	0.101	0.510	0.9	0.100	0.201	0.9
	March	0.100	0.499	0.9	0.141	0.171	0.9
	April	0.247	0.468	0.9	0.207	0.135	0.9

Table 4. Forecasting Results

Year	Month	Inner Item	Outer Item	Year	Month	Inner Item	Outer Item
2023	May	0.7412	0.85283	2024	January	0.587	0.26029
	June	0.499	0.81638		February	0.348	0.57648
	July	0.5824	0.61798		March	0.4359	0.46478
	August	0.768	0.81964		April	0.2755	0.43549
	September	0.766	0.85005		May	0.3474	0.30567
	October	0.6775	0.60767		June	0.2583	0.42151
	November	0.5072	0.34321		July	0.232	0.34136
	December	0.3921	0.29799		August	0.2972	0.28459
					September	0.1529	0.12292
					October	0.1487	0.12316
					November	0.1478	0.15166
					December	0.2452	0.23215

Table 5. Forecasting Results After Denormalization

Year	Month	Inner Item (Unit)	Outer Item (Unit)	Year	Month	Inner Item (Unit)	Outer Item (Unit)
2023	May	1599	278	2024	January	1262	118
	June	1069	267		February	738	204
	July	1251	216		March	931	173
	August	1658	269		April	579	166
	September	1654	278		May	737	131
	October	1460	212		June	542	162
	November	1087	141		July	484	140
	December	835	128		August	627	125
					September	311	81
					October	302	81
					November	300	89
					December	513	111

Table 6. Comparison of existing condition and demand forecasting results

Year	Month	Actual Demand		Year	Month	Forecasting Demand	
		Inner Item	Outer Item			Inner Item	Outer Item
2021	September	1502	287	2023	May	1599	278
	October	1114	268		June	1069	267
	November	1192	229		July	1251	216
	December	1623	276		August	1658	269
2022	January	1947	291		September	1654	278
	February	1365	222		October	1460	212
	March	1074	155		November	1087	141
	April	913	134		December	835	128
	May	1112	103	2024	January	1262	118
	June	805	192		February	738	204
	July	908	164		March	931	173
	August	653	153		April	579	166
	September	754	117		May	737	131
	October	537	169		June	542	162
	November	491	146		July	484	140
	December	653	139		August	627	125
2023	January	215	80		September	311	81
	February	198	75		October	302	81
	March	195	86		November	300	89
	April	517	104		December	513	111

The increase in demand is just a short distance from the actual data because the ANN method is iterated continuously until the demand results are close to the target data taken from the actual demand pattern so that the demand forecasting data is close to the actual demand data. In addition, the demand forecasting results are tested by finding the higher regression value and the minor MSE indicator to evaluate the results obtained from the model built.

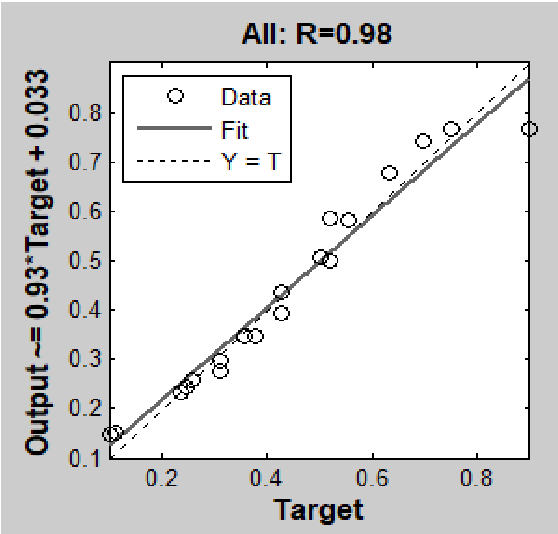


Figure 5. Item Input Regression Results

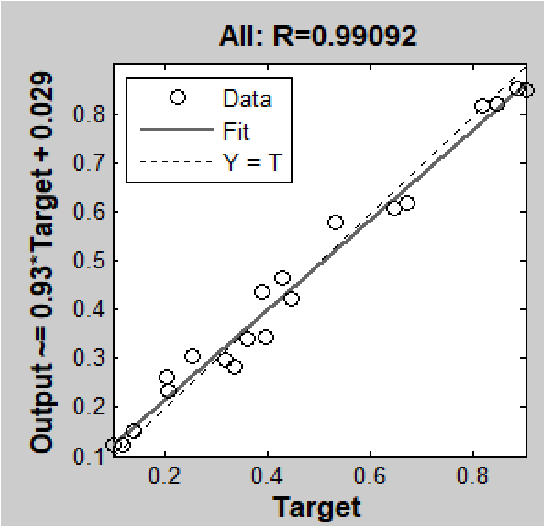


Figure 6. Item Output Regression Results

Figure 5 and Figure 6 are the regression results on the inner and outer items. Figure 5 shows that the regression value on the inner item that has been built is 0,98. While Figure 6 shows that the regression value on the outer item results in 0,99092, these two values explain that the level of correlation between the three input variables, such as demand data, inventory data, and hazardous waste data, is high in each item, which means there is a strong correlation or relationship between these variables and shows the level of accuracy in the calculation.

Results of Inventory Model use Continuous Review (s,Q)

1. Cost Data

Table 7 explains the cost data needed in the continuous review calculation, where there are 2 product items with different product prices because they have different characteristics and materials. In the ordering data, there are several needs for forklift borrowing costs and paper costs for purchase invoices, so the total ordering costs must be incurred are IDR 202,000. Then, the holding costs incurred by the company include electricity, cleaning, and land rental costs, which are included in the percentage of 25% of the product price per item.

The shortage costs incurred are caused by damage to goods when stored in the warehouse due to the accumulation of finished goods for too long, where there are damaged products on inner items, amounting to 260 units, and outer items, amounting to 121 units. Meanwhile, repair costs are assumed to be fixed, and each repaired item will cost the exact repair cost. Damaged products are caused by keys that do not fit or nails that are worn out, so rivet pliers are needed to replace the nails or keys when making repairs. Therefore, if a product is damaged by one of these damages, the remaining cost will be included in the depreciation of the rivet pliers.

1. Holding Cost (O_h)

O_h = Holding Cost per unit x amount of inventory held

$O_{h(inner)}$ = Rp 5,000 x 7232

$O_{h(inner)}$= Rp 36,160,000/year

$O_{h(outer)}$ = Rp 24,750 x 1010

$O_{h(outer)}$= Rp 24,997,500/year

2. Ordering Cost (O_A)

O_A = Ordering cost x Ordering Frequency

O_A = Rp 202,000 x 3

O_A = Rp 606,000/year

Table 7. Cost Data

Cost Data	Type Cost	Cost
Product Price	Inner	Rp. 20,000
	Outer	Rp. 99,000
Ordering Cost	Unloading	Rp. 200,000
	Questionnaire Paper Cost	Rp. 2,000
Holding Cost	Inner	Rp 5,000
	Outer	Rp 24,750
Shortage Cost	Inner	Rp. 5,200,000
	Outer	Rp. 11,979,000
Repairing Cost	Key	Rp. 12,000
	Rivet Nails	Rp. 600
	Depreciation Rivet Pliers (3 Years)	Rp. 20,000

3. Shortage Cost(O_{cu})

O_k = Inventory shortage cost per unit of goods x The amount of shortage of goods in inventory

$O_{k(inner)}$ = Rp 20,000 x 260

$O_{k(inner)}$= Rp 5,200,000/year

$O_{k(outer)}$ = Rp 99,000 x 121

$O_{k(outer)}$= Rp 11,979,000/year

4. Repairing Cost

O_p = cost of repairing goods per unit of goods x number of damaged goods that can be repaired

O_p = Rp 32,600 x 121

O_p = Rp 3,994,600/year

5. Total Initial Inventory Cost (O_T)

O_T = O_h + O_A + O_k + O_p

$O_{T(inner)}$ = Rp 36,160,000 + Rp 606,000 + Rp 5,200,000

$O_{T(inner)}$= Rp 41,966,000/year

$O_{T(outer)}$ = Rp 24,997,500+ Rp 606,000 + Rp 11,979,000 + Rp 3,994,600

$O_{T(outer)}$= Rp 41,527,100/year

Based on the initial inventory calculation with actual demand from September 2021 to April 2023, the total initial inventory cost incurred by the company on inner items is IDR 41,966,000/year. On outer items, it is IDR 41,527,100/ year.

In addition, the calculation of the proposed inventory using the Continuous Review (s,Q) method is carried out by entering the number of requests before forecasting and after forecasting to see if there is a change in the order lot and total inventory cost by achieving the objective function using the Continuous Review (s,Q) method. The total inventory cost of the proposed outside items is considered as the cost of repairs. Product repair costs are included in shelf costs because they relate to maintaining inventory to keep it in a saleable condition [5]. Damaged products in outer items are caused by prolonged storage, so repairing outer items is considered part of storage costs. The repair cost arises when there are a certain number of damaged products due to too long accumulation in the warehouse (b) and the repair cost per unit (p).

$$Op = b \times p \quad (10)$$

Meanwhile, the expected repair cost is obtained from the repair cost per unit (p) by the expected number of repair units E(x), with the E(x) obtained by the average demand rate per unit of time (λ) and the condition probability of the number of defective products in a given period (Pr) [6].

$$Op = p \times E(x) \quad (11)$$

$$E(x) = \lambda \,.\, T.\, (1 - Pr) \quad (12)$$

Thus, the equation for the expected total inventory cost considering repair items is obtained as follows.

$$Min\ Z = \frac{AD}{qo} + h(\frac{1}{2}\,qo + r - DL) + \frac{CuD}{qo}\,x\,1 + P \times (\lambda.T.(1 - P_{repair})) \quad (13)$$

From the calculations, the company experienced a decrease in total inventory costs on each product item.

The Continuous Review (s,Q) policy is a flexible policy where when inventory reaches the reorder point (r) or the reorder point can be ordered as much as Q raw materials so that the ordering of raw materials can be adjusted to the number of damaged products that can be repaired. Therefore, calculations are made based on Table 8 of the decision variables obtained with a reorder point on Inner items of 882 units and Outer items of 161 units. In addition, the number of booking lots generated for Inner items is 1257 units, and Outer items are 189 units in the existing condition. Then, in forecasting the period May 2023 to December 2024, the reorder point value for Inner items is 876 units, and Outer items are 158 units. After that, the optimal order quantity value generated for Inner items is 1371 units, and for Outer items, it is 188 units under forecasting conditions. The decision variables will affect the expectation of the total cost of inventory, where the expectation of the total cost for each item decreases.

Figure 7 proves that the Continuous Review (s,Q) objective function with minimization of total inventory costs is achieved, which occurs due to a reduction in the accumulation of goods in the warehouse and a decrease in damaged products, which causes a decrease in storage costs and shortage costs. It was obtained that the initial total inventory cost on inner items was IDR 41,966,000/year while the results before forecasting decreased by 83% by IDR 7,279,956/year, and after forecasting from the period May 2023 to December 2024 decreased by 81% by IDR 7,792,279/year.

Table 8. Result Decision Variables

Decision Variables	Proposed Condition Before Demand Forecasting		Proposed Condition After Demand Forecasting	
	Inner	*Outer*	*Inner*	*Outer*
Order Quantity	1257	189	1371	188
Reorder Point	882	161	876	158

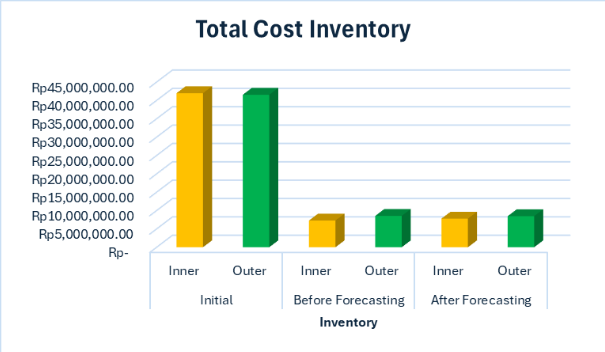


Figure 7. Comparison Results of Total Overall Inventory Cost

In external items, the total inventory cost has decreased by 79% by IDR 8,534,097/year, and after forecasting, it has decreased by 80% by IDR 8,463,151/year from the initial total inventory cost of IDR 41,527,100/year. The total inventory cost that considers repair items caused by the accumulation of finished goods in the warehouse differs from the research [6] [7], which considers repair products caused during the production process and the delivery of raw product materials. The calculation of product improvements can reduce shortage costs and replace them with repair costs to reduce lost sales.

CONCLUSION

The medical industry company has excess inventory in the warehouse, which causes damaged products and high total inventory costs. The buildup occurs because the company continues to reorder with the previous order lot number. After all, the company does not have an inventory policy, causing a buildup of finished goods in the warehouse. Therefore, demand forecasting and designing inventory policies consider repair items caused during the buildup of finished goods in the warehouse.

Based on the results of demand forecasting calculations using the ANN method, the amount of future demand is obtained with a high correlation value and the smallest MSE value, namely for inner items of 0.98 and MSE value of 0.00078 for outer items of 0.99092 and MSE value of 0.0013 which explains that each variable has a strong correlation. In addition, calculating order quantity and total inventory costs using the continuous review (s,Q) method resulted in considerable savings. The decrease is due to adding repair cost variables to the calculation of the order quantity and total inventory cost for repairing usable items so that future shortage costs and repair costs will experience a decrease in the total inventory cost of each item. The calculation results of the total cost of the proposed inventory on inner items before and after forecasting show a decrease in the total cost of the proposed inventory from the initial total cost of inventory to 83% and 81%. The total cost of inventory proposed before and after forecasting for outer items decreased by 79% and 80% from the initial total inventory cost. Reducing the total cost of inventory will increase profits and increase cost efficiency for the company. In addition, with continuous review (s,Q) inventory system by considering repair items caused by the accumulation of finished goods in the warehouse.

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