SINERGI Vol. 28, No. 2, June 2024: 219-230
http://publikasi.mercubuana.ac.id/index.php/sinergi
http://doi.org/10.22441/sinergi.2024.2.002

Drug forecasting and supply model design using Artificial Neural Network (ANN) and Continuous Review (r, q) to minimize total supply cost

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Abstract
The Mentawai Islands Regency Regional General Hospital faces a significant challenge with an 83% overstock of Medical Consumables, leading to increased inventory costs and potential damage and expiration of items. This exceeds the 1% pharmaceutical drug storage standards the Ministry of Health set. This study aims to optimize demand forecasting and minimize total inventory costs through a two-stage process. Firstly, demand forecasting is conducted using Artificial Neural Network (ANN), predicting a future demand of 10,036 units of Medical Consumables. Subsequently, the optimal order quantity and reorder points are calculated using the continuous review (r, Q) approach. The results reveal the optimal order quantities and reorder points for four types of Medical Consumables. This research introduces a novel approach by employing ANN for demand forecasting, then calculating optimal order quantities and reorder points using continuous review (r, Q). The cost components considered in the inventory cost calculation include purchasing cost, holding cost, shortage cost, order cost, outdating cost, and inspection cost. The designed forecasting models aim to enhance inventory management efficiency, optimize cost control, and improve patient services. The limitation of this research is that it only used five types of consumable medical materials to carry out this research due to limited data access. It is hoped that future research can use other types of drugs as well as a periodic review and forecasting approach using GA.

Keywords:
Artificial Neural Network;
Continuous Review;
Forecasting;
Order Quantity;
Reorder Point;

Article History:
Received: July 23, 2023
Revised: November 26, 2023
Accepted: November 30, 2023
Published: June 2, 2024

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INTRODUCTION

Mentawai Islands Regency Hospital has a Pharmaceutical Logistics division in charge of providing medicines needed by patients of the Mentawai Islands Regency Hospital. The drugs available in the pharmacy of the Mentawai Islands Hospital are Tablets, Syrups, Ointments, Injections, Liquids, *Medical Consumables*, reagents, and Dentistry materials. Drugs are an essential component that must be available in health services. Drugs become a link between patients and healthcare facilities because the availability or absence of drugs in healthcare facilities will positively or negatively impact the quality of service [1]. Therefore, good and correct drug management is needed to ensure the continuity of availability and affordability of drug services. Damaged drugs can no longer be used because of damage accompanied by changes in shape, color, odor, taste or consistency.

Figure 1 shows the percentage of expired drugs in 2022, where there are five types of drugs whose percentage is above the tolerance limit: Tablets 9%, Syrup 34%, Injection 19%, Liquid 9% and *Medical Consumables* 15%. According to the pharmaceutical drug storage standards set by the Ministry of Health Decree No. 1197/SK/X/2004, the percentage of expired drugs is still acceptable if the percentage value of expired drugs is below 1% of the total inventory.

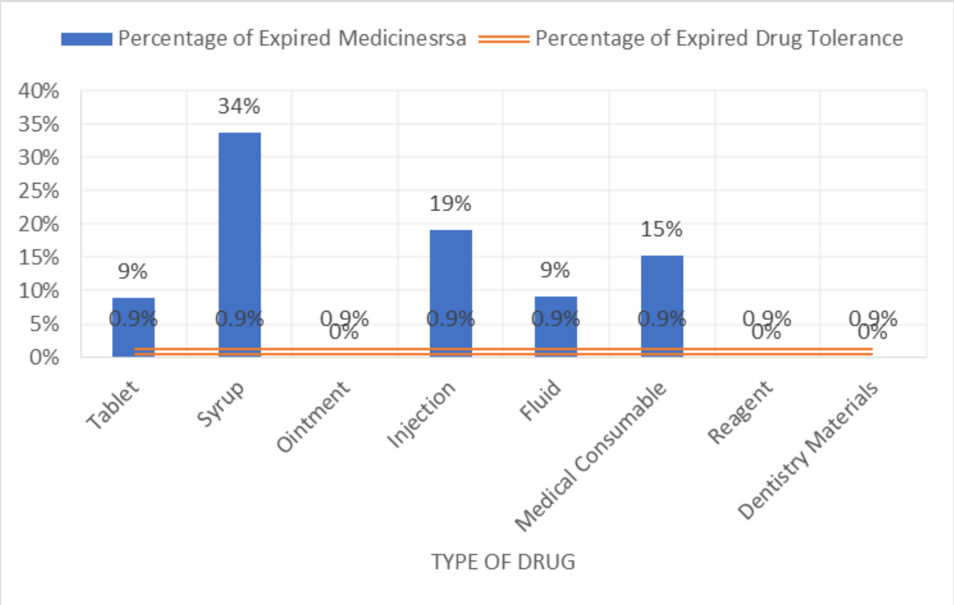

Figure 1. Percentage of Expired Medicines in 2022

If the percentage of expired drugs is above 1%, it indicates ineffectiveness and efficiency in managing drug supplies. This happens because drug evaluation is still not optimal, and drug stock data collection is not accurate. Where when collecting drug data, there is information about drugs that have not been inputted, such as how many drugs have entered and left. Hence, the data is incomplete, and there is a lack of supervision and monitoring of drugs that are about to expire or do not report them in a timely manner, making purchases when supplies are still available, and excessive purchase amounts.

The occurrence of expired drug stocks can cause material losses. Material losses in drug supplies are losses that occur physically or materially that cause financial losses to the Mentawai Islands Hospital. One of the factors causing material losses in drug supplies is expiration. If the drug is not used before the expiration date, then the drug is considered ineffective and must be disposed of.

Table 1 shows the financial loss because drugs that are still suitable for use cannot be utilized. The most significant loss occurred in the type of drug Consumable Medical Materials, which amounted to IDR 45,033,866.95. Consumable Medical Materials had the largest loss due to the high cost or purchase price compared to other types of drugs. *Medical consumables* are devices intended for single use (single use) (PMK N0. 58 of 2014). The cause of expired *Medical Consumables* with a percentage of expiration above 1% is 15% due to overstock of 83%. The difference between total inventory and usage can cause damage to *Medical Consumables* inventory because these items have an expiration time.

In mathematical modeling for perishable goods (food, vegetables, grains, etc.), the rate of deterioration plays an important role in the optimal policy. Inefficient procurement problems can affect the inefficiency of drug procurement [2] [3]. Fluctuating demand is one of the factors that cause inefficiency [4][5], and it is necessary to do accurate demand forecasting in planning [6, 7, 8, 9]. Based on research conducted by [10] determines the amount of hospital and pharmacy supplies where there is an imbalance between demand and supply. In addition, research to reduce inventory costs also applies a continuous review inventory system [11, 12, 13, 14, 15] because the actual condition considers fixed lifetime and normally distributed demand.

Based on the problems described earlier, the solution to this problem is to design a drug demand and inventory forecasting model using artificial neural networks and continuous review to reduce total inventory costs.

Table 1. Disadvantages of Expired Medicine

Type of Medicine	Loss (IDR)	Percentage Expired (%)
Tablet	3,620,814.11	9
Syrup	7,481,544.30	34
Ointment	0	0
Injection	24,693,892.74	19
Fluids	1,468,575.05	9
Medical Consumables	45,033,866.95	15
Reagents	0	0
Dentistry Materials	0	0

Table 2. Literature Review

Research		1 [16]	2 [17]	3 [18]	4 [19]	5 [20]	6 Proposal models
Product Type	Perishable	✓	✓	✓	✓	✓	✓
Demand Forecasting (ANN)	yes						✓
	no	✓	✓	✓	✓	✓	
Method	Continuous review	✓					
	Periodic review		✓	✓		✓	
	FEFO						
	EOQ						✓
Objective Function	Minimization of Total Inventory Cost				✓	✓	✓
	Increase Profit	✓	✓	✓			
Decision Variable	Optimal reorder point						✓
	Optimal Order Quantity	✓	✓	✓	✓	✓	✓
	Inventory Level				✓		
	Cycle length	✓					
Demand	Probabilistic				✓		✓
	Stochastic		✓	✓		✓	
	Deterministic						
Leadtime	Probabilistic						
	Stochastic			✓			
	Deterministic	✓	✓			✓	✓
	Zero		✓		✓		
Lifetime	Probabilistic						
	Stochastic						
	Deterministic	✓	✓	✓	✓	✓	✓
Number of products	Single item	✓					
	Multi item		✓	✓	✓	✓	✓
Inventory cost	Ordering cost	✓	✓	✓	✓	✓	✓
	Holding cost	✓	✓	✓		✓	✓
	Purchase cost	✓		✓	✓		✓
	Shortage cost	✓	✓				✓
	Outdate cost		✓		✓	✓	✓
	Cost motivation strategy					✓	
	Commuting cost					✓	
	Inspection cost	✓					✓
	Emergency cost				✓		

Table 2 shows the contribution of this research, which integrates several theories, namely the integration of ANN and Continuous Review methods, as well as the addition of purchase cost, holding cost, order cost, outdated cost, shortage cost, inspection cost component variables, with the objective function of reducing total inventory cost.

MATERIAL AND METHOD

Material

Consumable Medical Materials are medical devices intended for single use, the list of products of which is regulated in laws and regulations including Sterile Handscoon 7.5/Tro-sensosurge (*Medical Consumables*-1), sterile surgical glove 7.5/2020 (*Medical Consumables* -2), Handscoon No Sterile/2020 (*Medical Consumables*-3), Supercare Surgical Face Mask/Earloop 3 Ply/2020 (*Medical Consumables*-4).

Methods

The methods used in this study are Artificial Neural Networks (ANN) to forecast the demand for Consumable Medical Materials and continuous review (r, Q) to determine the order quantity and reorder point. An ANN is a mathematical model inspired by the workings of the nervous system in the human brain. ANN is used to model and process complex data with the ability to learn from patterns or relationships contained in the data. In the context of demand forecasting, ANN is used to predict the amount of future demand based on input data such as sales history or previous orders [21].

Forecasting with ANN involves several stages, including data processing, model training, and evaluation. The reason for choosing the ANN method for forecasting is that it has a smaller error value than other forecasting models [22, 23, 24, 25]. While the reason for choosing the continuous review method (r, Q) is because the existing conditions have a fixed lifetime and fixed leadtime and are perishable products [26][27].

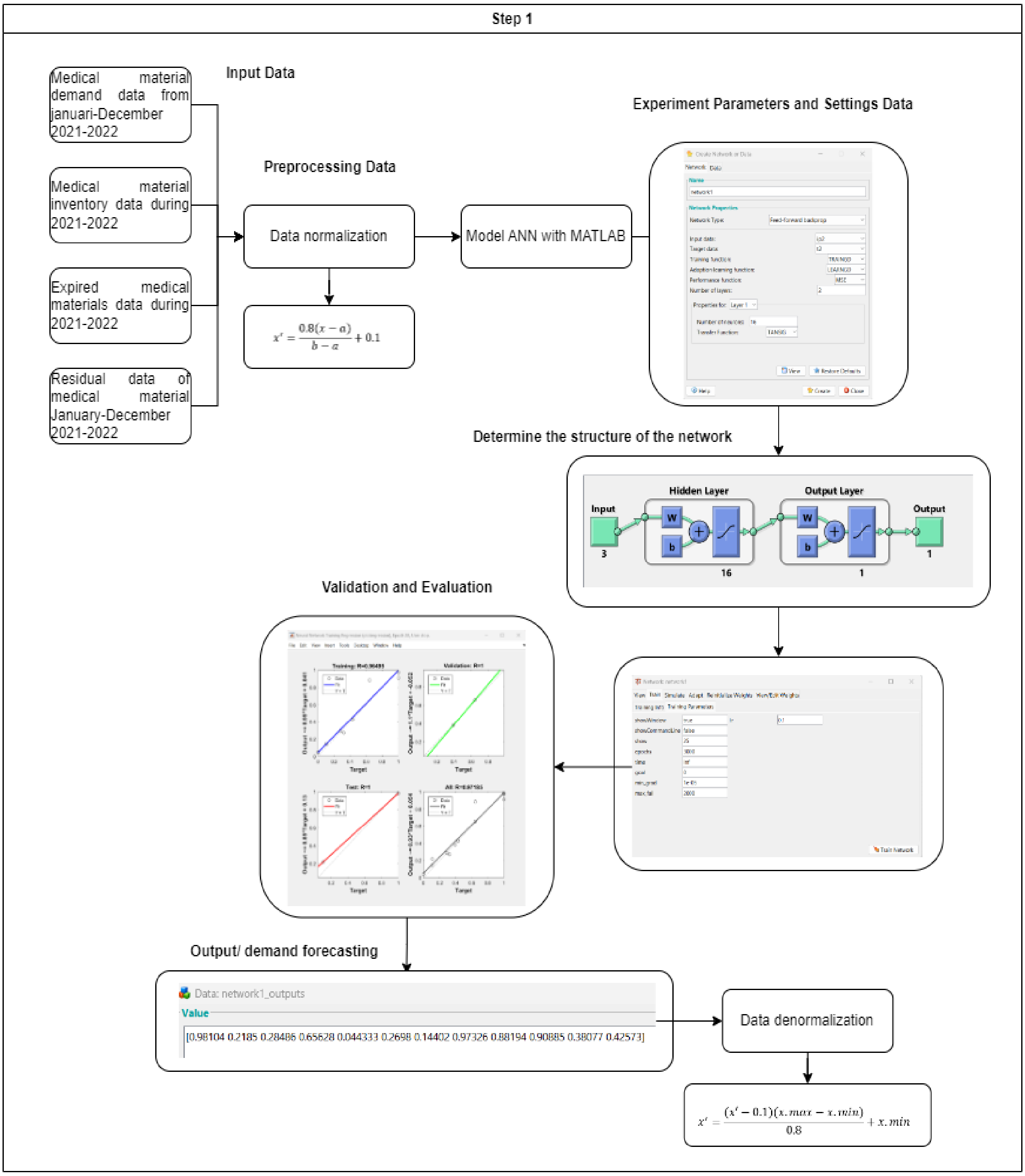

Figure 2. Block Diagram of the ANN

Research Stages

Stages 1

Figure 2 shows a block diagram explaining the stages of the research process. First, in conducting this research, namely collecting input data for demand forecasting with ANN, the data used is secondary data, including data on remaining stock at the end of each month, data on the number of expired Consumables at the end of 2021-2022, data on demand for Consumables in 2021-2022, data on the amount, of Consumables in 2021-2022. The data that has been collected will be normalized to facilitate calculations by transforming the values of all input and output data into the range of zero and one, using the normalization formula.

$$x' = \frac{0.8(x-a)}{b-a} + 0.1 \tag{1}$$

Where x' is normalization value n, x is data value n, a is the lowest data value, b is the highest data value, 0.8 is determination.

Table 3. Experiment Parameters and Settings Data

Parameters	Experiment Set
Number of nodes in the hidden layer	1,2,3,4,5
Training function	*Trainbfg and Trainlm*
Activation function	*Tansig and logsid*
Performance function	*Mean Squared Error*
Learning function	*Learngdm and learngd*
Maximum Epoch	3000

After the data is normalized, the parameters in MATLAB 2016, where the parameters used are the training, activation, performance, and learning functions, are determined.

Table 3 determines the parameters located in the hidden layer using the trial-and-error method, where each parameter is tested and paired with each other to get forecasting results with the smallest error value. The changed parameters are the number of nodes in the hidden layer and training, activity, performance, and learning functions.

After the parameter set is run, they conduct validation and evaluation. The regression value will be checked, and if the regression value is close to one, the related variables will be correlated. Furthermore, the results of demand forecasting for the next 12 months will be denormalized.

$$x' = \frac{(x' - 0.1)(x.max - x.min)}{0.8} + x.min \qquad (2)$$

Stages 2

Figure 3 is an explanation of the second stage of this research, data collection to calculate the value of order quantity and reorder point, namely data on the price of Consumable Medical Materials, which is used in this study in accordance with the price list of consumable medical materials in 2022. The data on the results of demand forecasting with ANN and lead time data is the waiting time the hospital requires when ordering products from suppliers until the product is received.

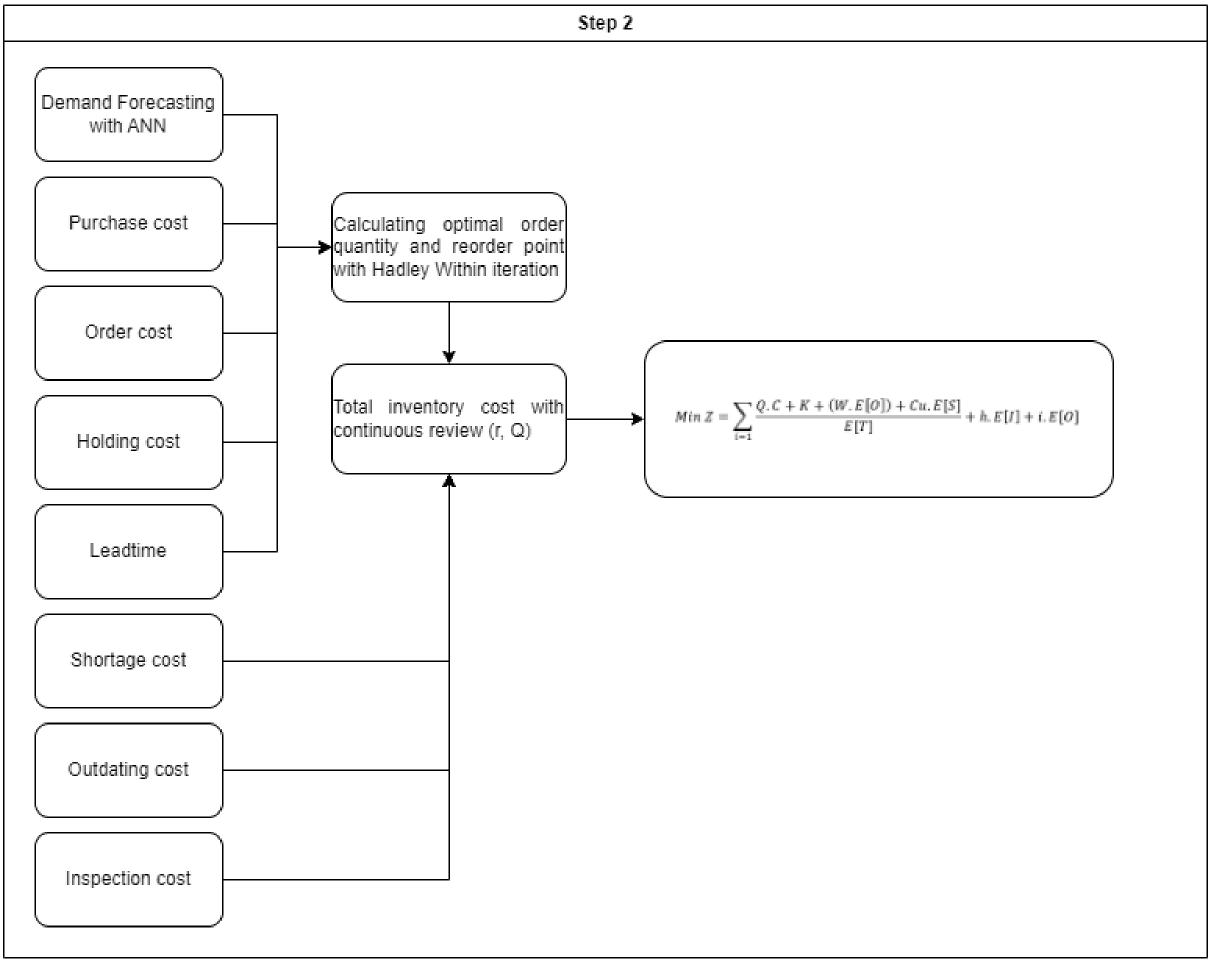

Figure 3. Block Diagram Continuous Review

This data is obtained from sources responsible for hospital pharmacy. Component Cost data used in research includes order costs, storage costs, shortage costs, expiration costs and inspection costs [14, 15, 16, 17]. After collecting data, the optimal order quantity and reorder point will be calculated using the Hadley-within iteration model. The formula is as follows:

i. Perform optimal order quantity calculations.

$$q01 *= \sqrt{\frac{2 \times A \times D}{h}} \quad (3)$$

Where q01 is optimal order quantity, A is order cost, D is demand, and h is holding cost.

ii. This process involves two main steps. First, we must determine the magnitude of the inventory shortage (α). Once the value of α has been determined, the next step is calculating the reorder point (r1).

$$\alpha = \int_r^\infty f(x)dx = \frac{h \times q01}{(Cu \times D)} \quad (4)$$

Where α Probability of shortage, qo1 is order quantity, Cu is shortage cost, D is demand, and h is holding cost.

$$r1 *= (D \times L \times T) + Z\alpha \times \sigma\sqrt{LT} \quad (5)$$

Where r1 reorder point, L is lead time, T is interval time, D is demand, Zα is Normal deviation, σ is sigma.

iii. Once r1 is obtained, the qo2 value can be calculated using the following formula.

$$q02 *= \sqrt{\frac{2 \times D[A + Cu \int_r^\infty (x - r1 *) f(x)dz]}{h}} \quad (6)$$

iv. This process involves two main calculations: calculating the value of alpha and estimating the value of r2.

$$\alpha = \int_r^\infty f(x)dx = \frac{h \times qo2}{(Cu \times D)} \quad (7)$$

$$r2 *= DLT + Z\alpha . \sigma\sqrt{LT} \quad (8)$$

v. Compare the values of r1 and r2. If the relative price equals r1, the iteration is complete, and r1= r2 and q1=q2 will be obtained. Otherwise, return to step 3 by replacing the r1 = r2 and q1 = q2.

Then, calculate the total cost of inventory with continuous review (r, Q) under the following conditions: normal distributed demand to reduce total inventory costs. The results of the proposed inventory will be compared with the existing inventory conditions. The number of consumable medical materials in 23 units is displayed only four, which is a limitation in this study.

RESULTS AND DISCUSSION

Results of forecasting model with ANN

The design of the architecture of the developed artificial neural network (ANN) model is adjusted to the pattern of inputs or inputs that will become outputs or outputs. To perform forecasting of demand for consumable medical materials. The first step in creating an artificial neural network is to determine the inputs and outputs entered during the training process using MATLAB. Table 4 is the determination of the symbol on the input-output. The input data is normalized to produce numbers from zero to one, as seen in Table 5.

After the input data is processed, demand forecasting for the next 12 months will be produced. Table 6 shows the results of forecasting four Consumable Medical Materials for 12 months. Figure 4 compares the total demand in 2022 with the ANN forecast results.

Table 4. Input and Output Variables of Forecasting with ANN

***Input-Output* Model ANN (xn)**	**Description**
X1	Medical material demand data from January-December 2021-2022
X2	Medical material inventory data during 2021-2022
X3	Expired medical materials data during 2021-2022
X4	Residual data of medical materials January-December 2021-2022
Y’	The output of the ANN model is the target demand for the next month.

Table 5. Data Normalization

Medical Material Preparation	Input	1	2	3	4	5	6	7	8	9	10	11	12
Medical Consumables - 1	x1	0.86	0.00	0.71	0.00	0.00	0.14	0.57	0.29	1.00	0.29	0.57	0.00
	x2	1.00	0.85	0.81	0.68	0.64	0.60	0.55	0.43	0.36	0.19	0.11	0.00
	x3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	x4	2.00	1.96	1.81	1.77	1.72	1.66	1.53	1.45	1.26	1.17	1.04	1.00
Medical Consumables - 2	x1	1.00	0.11	0.29	0.64	0.00	0.32	0.11	1.00	0.64	1.00	0.39	0.43
	x2	1.00	0.83	0.80	0.74	0.63	0.62	0.56	0.53	0.36	0.24	0.07	0.00
	x3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
	x4	2.00	1.97	1.91	1.78	1.77	1.70	1.67	1.48	1.36	1.17	1.09	1.00
Medical Consumables - 3	x1	0.10	0.49	0.04	0.00	0.62	0.74	0.23	0.46	0.42	1.00	0.36	0.36
	x2	1.00	0.97	0.86	0.85	0.85	0.71	0.55	0.49	0.39	0.30	0.08	0.00
	x3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	x4	2.00	1.90	1.88	1.88	1.75	1.60	1.55	1.45	1.36	1.15	1.08	1.00
Medical Consumables - 4	x1	1.00	0.00	0.43	0.00	0.00	0.14	0.43	0.29	0.00	0.29	0.43	0.00
	x2	1.00	0.79	0.74	0.63	0.58	0.53	0.47	0.35	0.26	0.21	0.12	0.00
	x3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	x4	2.00	1.94	1.81	1.75	1.69	1.61	1.47	1.36	1.31	1.19	1.06	1.00

Table 6. Demand Forecasting Results with ANN

Month	*Medical Consumables -1*	*Medical Consumables -2*	*Medical Consumables -3*	*Medical Consumables -4*
1	838	31	4	885
2	174	3	36	182
3	741	8	1	441
4	177	23	0	184
5	178	1	51	184
6	236	9	65	240
7	617	3	13	449
8	338	31	37	331
9	919	23	33	187
10	350	32	82	335
11	643	12	28	459
12	190	13	29	190

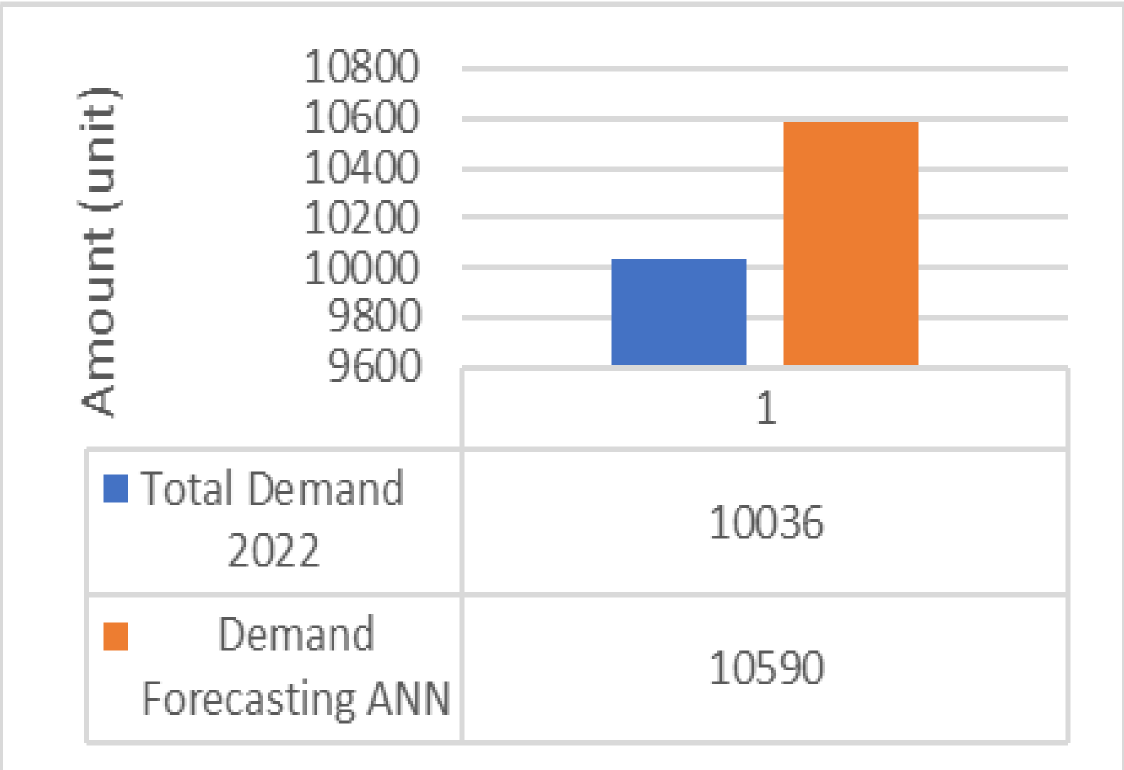

Figure 4. Comparison of 2022 Demand with Forecasting results

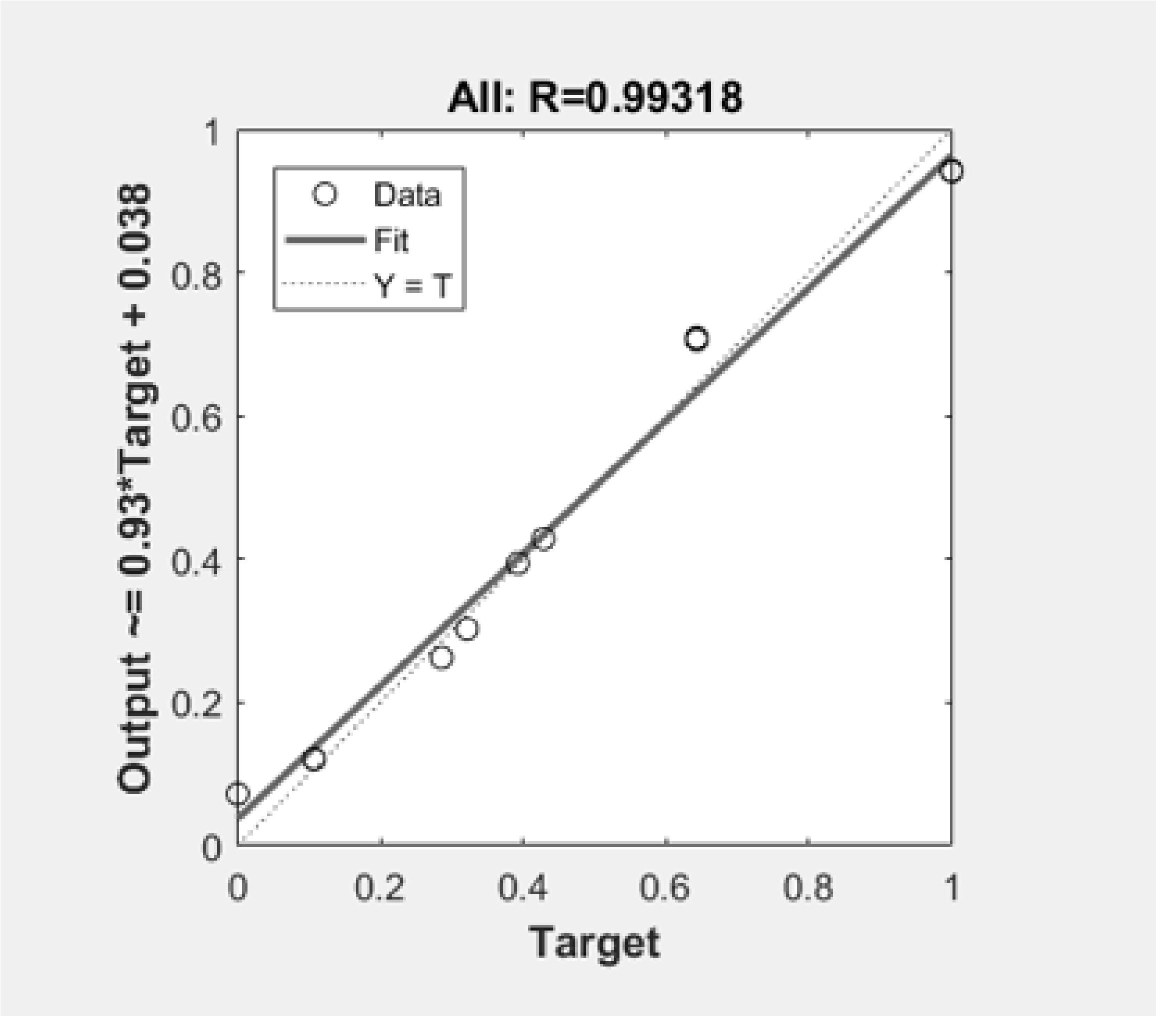

Figure 5. Regression Results

After the demand forecasting results are obtained, data testing is carried out to evaluate whether the prediction results of the model built using training data produce accurate results by calculating the forecasting error.

Figure 5 shows a regression of 0.99318, which means that the actual variables with the artificial neural network in the test have a reasonable correlation. The correlation size of 0.99318 indicates a high degree of association between the related variables, namely medical material demand data for 2022, medical material demand data from January-December 2022, medical material inventory data for a year, expired medical material data for a year, remaining medical material data January-December 2022.

Table 7 results trial-and-error values using the training function (trainbfg) and activation function (learngdm) where the smallest MSE value is 3.67 trainbfg_lerangdm_1.

Inventory model results with continuous review (r, Q)

The results of calculating optimal order quantity and reorder point using Hadley-within can be seen in Table 8. Table 8 explains that the Medical Consumables-1 replenishment policy will be ordered for as many as 1900 units if the stock is between 630 units. The basic formulation used to minimize total inventory costs is to divide the expected cycle cost by the expected cycle length.

$$TC(r,Q) = \frac{\text{Expected cycle cost}}{\text{Expected cycle lenght}} = \frac{K + cQ + pE[S] + wE[O]}{E[T]} + hE[I] \quad (9)$$

Expected cycle cost is a cost expectation consisting of order cost (K) is the cost incurred when ordering medical materials in one order, purchase cost (c) is the cost incurred to buy medical materials in the optimal order quantity, lost sales cost (p) is the cost incurred in the event of a shortage of medical materials, the expected number of shortages E[S], Outdating cost (w) is the cost incurred due to expired medical materials, the expected number of expirations E[O].

E[T] is the expected cycle length, holding cost (h) is the cost of storing medical materials, and expected inventory level E[I]. The proposed formulation model adds a cost variable, namely inspection cost (i), which is the cost incurred to handle expired medical materials. This cost consists of destroying medical materials utilizing high-temperature incineration.

$$Min\ Z = \sum_{i=1} \frac{Q.C + K + (W.E[O]) + Cu.E[S]}{E[T]} + h.E[I] + i.E[O] \quad (10)$$

Table 9 shows the total inventory cost of four proposed consumable medical materials using forecasting, IDR 140,313,422. Table 9 shows the total cost of the existing inventory of four Consumable Medical Materials, IDR. 153,829,771, where the Mentawai Head Hospital can save 8.7% of inventory costs after determining the order quantity and reorder point. The difference in total inventory costs of IDR. 13,516,349 is influenced by the number of Medical Material shortages and expiration expectations at the end of the period. The explanation for each component of inventory costs is in Table 11.

Table 7. MSE results trainbfg_learngdm

													Amount	MSE
						trainbfg_learngdm_1								
Error	0.28	0.23	0.07	0.16	0.21	0.05	0.21	0.29	0.01	0.25	0.23	0.01		
denormalization	7	5	0	3	5	0	5	8	0	6	5	0	44.09	3.67
						trainbfg_learngdm_2								
Error	0.30	0.36	0.08	0.17	0.29	0.06	0.26	0.35	0.02	0.27	0.26	0.02		
denormalization	7.80	9.70	0.28	3.35	7.49	0.00	6.34	9.33	0.00	6.71	6.34	0.00	56.97	4.75
						trainbfg_learngdm_3								
Error	0.46	0.35	0.10	0.20	0.46	0.07	0.35	0.36	0.06	0.36	0.37	0.03		
denormalization	13.18	9.35	0.99	4.37	13.11	0.00	9.35	9.72	0.00	9.70	10.17	0.00	79.44	6.62
						trainbfg_learngdm_4								
Error	0.57	0.35	0.09	0.19	0.36	0.08	0.79	0.35	0.05	0.33	0.46	0.03		
denormalization	16.84	9.33	0.72	4.00	9.70	0.32	24.36	9.35	0.00	8.71	13.08	0.00	96.40	8.03
						trainbfg_learngdm_5								
Error	0.55	0.25	0.06	0.25	0.37	0.03	0.44	0.29	0.01	0.25	0.23	0.01		
denormalization	16.17	5.96	0.44	5.94	10.17	0.00	12.44	7.61	0.00	6.01	5.45	0.00	69.31	5.78

Table 8. Optimal Order Quantity and Reorder Point

Medical Material Preparation	***Medical Consumables-1***	***Medical Consumables -2***	***Medical Consumables -3***	***Medical Consumables -4***
Optimal Order Quantity	1900 unit	50 unit	100 unit	2050 unit
Reorder point	630 unit	10 unit	55 unit	345 unit

Table 9. Total Cost of Proposed Inventory

Medical Material Preparation	***Medical Consumables -1* (IDR)**	***Medical Consumables -2* (IDR)**	***Medical Consumables -3* (IDR)**	***Medical Consumables -4* (IDR)**
Holding Cost (Hs)	297,498.03	290,437.00	293,292.10	143,203.35
Order Cost (Op)	73,333.33	135,206.56	129,823.11	85,714.29
Shortage Cost (Ok)	4,836,333.33	1,565,990.91	-	1,413,214.29
Outdating cost (Otc)	19,785.00	-	-	19,785.00
Purchasing Cost (Pc)	36,272,500.00	33,059,808.10	32,000,000.00	29,677,500.00
inspection cost (Ic)	-	-	-	-
Total Cost	1,499,449.70	5,051,442.57	32,423,115.21	31,339,416.92

Table 10. Total Cost of Existing Inventory

Medical Material Preparation	***Medical Consumables -1* (IDR)**	***Medical Consumables -2* (IDR)**	***Medical Consumables -3* (IDR)**	***Medical Consumables -4* (IDR)**
Holding Cost (Hs)	2,901,800.00	2,783,983.84	3,200,000.00	2,374,200.00
Order Cost (Op)	20,000.00	20,000.00	20,000.00	20,000.00
Shortage Cost (Ok)	-	-	-	-
Outdating cost (Otc)	-	1,739,989.90	-	-
Purchasing Cost (Pc)	36,272,500.00	34,799,798.00	40,000,000.00	29,677,500.00
inspection cost (Ic)	-	5,000.00	-	-
Total Cost	39,194,300.00	39,343,771.74	43,220,000.00	32,071,700.00

Table 11. Cost of Inventory Components

Cost Component	Existing (IDR)	Proposal (IDR)
Holding Cost	11,259,983	1,024,430
Order Cost	80,000	424,077
Shortage Cost	-	7,815,538
Outdating cost	1,739,989	39,570
Purchasing Cost	140,749,798	131,009,808
inspection cost	5,000	-
Total	153,834,771.74	140,313,424.40

Table 11 explains the gap between the components of inventory costs where the coding cost has decreased by 90%. This occurs because when the proposed inventory conditions are met, the amount of storage of consumable medical materials is less than the existing conditions. The order cost has increased from IDR. 80,000 to IDR. 424,077.29, when the existing conditions only make one order, while the proposed conditions have a frequency of ordering more than once because previously, the optimal number of orders was determined in one message to meet demand.

The shortage cost from IDR.0 to IDR. 7,815,538.53 occurred because, in the existing condition, there was no shortage of Consumable Medical Materials. After all, the amount of inventory exceeded demand. After calculating the optimal order quantity inventory policy, there was an expectation of a shortage. Expiry costs when the existing conditions are IDR. 1,739,989 have decreased by IDR. 39,570. This is because the order quantity in the proposed inventory has been determined to minimize the number of expired medical materials. Purchasing costs have decreased by IDR. 9,739,990. This is because the optimal order quantity has been determined in the proposed conditions so that it can save on purchasing costs.

CONCLUSION

The problem at the Mentawai Islands Hospital is that there are expired drugs, namely medical consumables, which account for 15% of the total inventory, resulting in losses. This happens because the amount of inventory exceeds demand, so the overstock is 83%. The researcher designs a demand and inventory forecasting model using JST and Continuous Review (r, Q) to solve the problem at hand. With the design of demand and inventory forecasting models, it is hoped that inventory management will run more efficiently, control costs more optimally and improve patient services.

Based on the research results to forecast the demand for Consumable Medical Materials with the JST model, a gap of 554 units of Consumable Medical Material inventory with a demand of 2022 is obtained, where the results are accurate because the correlation value is 0.99. The results of determining the order quantity and reorder point with continuous review (r, Q) can reduce inventory costs. The results show that the inventory costs have decreased by 8.7% from the existing conditions. In addition to reducing inventory costs, this continuous review inventory system also considers shortage and expiration costs.

ACKNOWLEDGMENT

I want to thank the Mentawai Islands Regency Hospital for collecting the data needed for this research, and I would also like to thank my supervisor, who helped me complete this research well.

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