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Design of Economic Order Quantity on Polyester Yarn Raw Material Based on Artificial Neural Network Forecasting

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Abstract – **Polyester yarn is a key raw material in textile manufacturing due to its durability and affordability. PT ABC relies on external suppliers for polyester yarn, making inventory management crucial for production efficiency. However, the company's current ordering approach has led to occasional stock shortages, impacting operations. This study develops an inventory control model using the Economic Order Quantity (EOQ) method, incorporating safety stock and reorder point calculations to minimize stockouts and reduce inventory costs. Additionally, Artificial Neural Networks (ANN) are used to forecast demand for 2022, improving estimation accuracy. Based on historical demand data from 2019 to 2021, the EOQ method lowers inventory costs compared to the company's approach, achieving efficiency gains of 19%, 12%, and 29%, saving IDR45,745,000, IDR23,735,000, and IDR98,020,000, for each respective year. The ANN model utilizing the TrainLM training function achieves the lowest Mean Squared Error (MSE) of 0.063528 and forecasts a total raw material requirement of 2,510,628 kg for 2022. The EOQ value for 2022 is set at 44,817 kg, with safety stock and reorder point levels of 8,438 kg and 29,360 kg, respectively.**

Keywords – *Artificial Neural Network, Economic Order Quantity, Inventory, Reorder Point, Safety Stock.*

INTRODUCTION

Polyester yarn is one of the yarns used to produce various types of garment products. There are 2 types of clothing that require polyester yarn, i.e., clothes made with 100% polyester yarn and clothes that combine polyester yarn with other yarns. Polyester yarn used as a clothing material has a number of advantages, namely: [1] not easy to shrink, [2] affordability and [3] may be used in a variety of clothes. Thus, it creates an opportunity for textile companies to reap profits by using polyester yarn to meet its demands [1], [2].

PT ABC is a company engaged in the textile and garment industry. The polyester yarn produced by this company accounts for 70% of the total production as it is produced continuously. This company, in addition to producing yarn to meet demands for its own derivative products, also produces other derivative products to meet demands from its Business-to-Business customers [3]. PT ABC does not produce their own raw materials for the yarn production, instead they are supplied by other companies. Therefore, availability of raw materials is affected by supplier factors. Inventory control carried out by PT ABC includes purchasing of raw materials when the inventory stock is expected to run out in a certain period of time, while the average quantity of raw materials ordered is based on their usual order, which is 20,000 kg or based on production requests from the marketing department. This has led to a few times of stockouts. The condition of being out of stock is often experienced by various industries, including the retail industry [4], the fashion and apparel industry [5], the food industry [6] and several manufacturing industries [7]. Therefore, this study aims to determine the economic order quantity (EOQ) for Polyester Yarn Raw Material.

Therefore, it is necessary to implement an inventory control method, one of which is the Economic Order

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Quantity method. Previous research has implemented the EOQ model based on its findings in the perishable industry [8], dairy product industry [9], soybean industry[10] and repair and waste disposal industry [11]. To determine effectiveness of the implementation, this study initiated with comparing the total inventory cost using The EOQ Method to that using company's method based on historical data on the use of polyester yarn raw materials from 2019 to 2021.

The company relies on its marketing team to plan market demands over a weekly to monthly period. Although it has proven to be effective, the planning process requires significant resources. Therefore, in this study, monthly demand for polyester yarn was forecasted throughout 2022 using the Artificial Neural Networks [12]. Several studies have successfully implemented ANN models in the textile industry for activities such as production maximization [13], forecasting [12], [14], operational modernization [15] and energy sustainability [16].

Following the implementation plan of the inventory control method, it is necessary to determine the economic order quantity and calculate the total inventory cost based on the forecasting results for 2022. In addition, it is also necessary to determine the value of safety stock [17]–[19] and reorder point [19]–[21] to prevent the company from stockout. This step was carried out based on the results of demand forecasting using an artificial neural network.

This study aims to: compare total inventory costs using the EOQ method versus the company's current approach based on historical raw material usage from 2019 to 2021, forecast monthly polyester yarn demand for 2022 using ANN implemented in MATLAB 2016, determine the EOQ value and calculate total inventory costs based on the 2022 forecast results and tle last is establish safety stock levels and reorder points for polyester yarn raw materials based on demand forecasts for 2022.

METHOD

The main focused object on in this research is Polyester yarn. This study began with comparing the total inventory cost produced by the company's method with The Economic Order Quantity (EOQ) Method based on historical demand data for Polyester yarn production.

This step was taken to determine the effectiveness of the application of the EOQ method in the company in minimizing the total of inventory cost as previous researchers did. The next step was forecasting demand with an artificial neural network. Forecasting began with training the input data to get the best forecasting performance then testing it using test data and selecting the network that produces the smallest Mean Square Error (MSE) value.

After getting the forecasting results, the next step was to calculate the EOQ value to be determined and calculate the total inventory cost. In addition to determining the value of EOQ, at the final stage, this study also set the value of safety stock and reorder point so that stock out problems will not occur again.

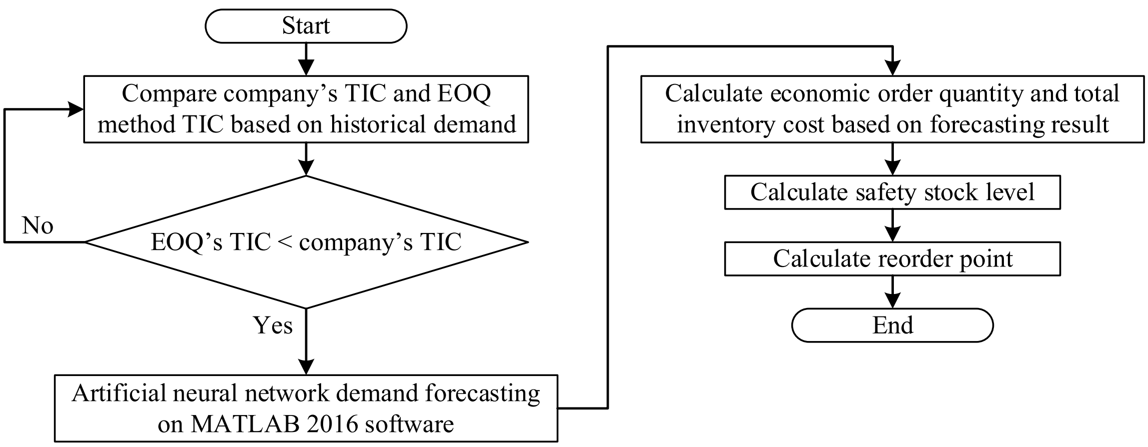

Figure 1. Research Methodology

RESULT AND DISCUSSION

Comparing Total Inventory Cost of Company's Method and Economic Order Quantity's Method

Historical demand data used in calculating total inventory cost was generated from monthly demand data taken in 2019 - 2021. In addition to historical demand data, there was also inventory data variable, which is ordering cost of raw material per order, IDR 2,000,000 and holding cost of raw materials, IDR 50,000,000. Historical demand production data shown in table 1.

Table 1. Historical Production Demand

No.	Date	Demand (*bale*)	Raw Material (kg)
1	Jan-19	849	157.853
2	Feb-19	774	143.923
3	Mar-19	886	164.707
4	Apr-19	855	158.982
5	May-19	806	149.959
6	Jun-19	690	128.409
7	Jul-19	796	148.056
8	Aug-19	879	163.542
9	Sep-19	939	174.654
10	Oct-19	943	175.398
11	Nov-19	989	183.978
12	Dec-19	975	181.322
13	Jan-20	974	181.250
14	Feb-20	925	172.050
15	Mar-20	1.123	208.841
16	Apr-20	102	18.972
17	May-20	27	4.992
18	Jun-20	215	39.990
19	Jul-20	304	56.600
20	Aug-20	0	0
21	Sep-20	545	101.389
22	Oct-20	1.101	204.693
23	Nov-20	1.149	213.714
24	Dec-20	1.170	217.620
25	Jan-21	1.202	223.583
26	Feb-21	1.167	217.062
27	Mar-21	1.208	224.595
28	Apr-21	1.195	222.359
29	May-21	959	178.394
30	Jun-21	1.294	240.703
31	Jul-21	1.322	245.925
32	Aug-21	1.277	237.529
33	Sep-21	1.431	266.166
34	Oct-21	1.464	272.390
35	Nov-21	1.440	267.918
36	Dec-21	1.518	282.348

To calculate the EOQ value, the storage cost has to be in IDR/unit of raw material/year, while the storage cost is in IDR/year. In this study, they were converted by assuming that the average raw material stored in the warehouse per day was 10,000 kg. This was based on the average order of 20,000 kg made by the company and the average daily use of raw materials of 10,000 kg, allowing an annual storage cost of raw materials of 5,000/kg/year. The total inventory cost consists of the total ordering cost and the total holding cost. The total ordering cost is obtained by calculating the frequency of orders using Equation (1) and Equation (2) to calculate the total ordering cost [22].

$$f = \frac{D}{Q} \quad (1)$$

Where:
f = order frequency in year
D = quantity of raw material usage per year
Q = quantity ordered

$$TC = f \, x \, C \quad (2)$$

Where:
TC = total cost
C = order cost

The total inventory cost from 2019 to 2021 which were calculated using the company's method, consecutively, were IDR 244,000,000, IDR 194,000,000, and IDR 338,000,000. Meanwhile, using The EOQ Method, need to know the EOQ value first, then can calculate the Total Inventory Cost. EOQ value calculated using Equation (3) [22].

$$Q^* = \sqrt{\frac{2CR}{H}} = \sqrt{\frac{2CR}{PF}} \quad (3)$$

Where:
Q^* = economic order quantity (EOQ)
C = order cost
R = annual demand
H = holding cost
P = purchase cost
F = fraction

After knowing the EOQ value, then you can calculate the total ordering cost using Equations (1) and (2). While the total holding cost is calculated using Equation (4) [22].

$$Total\ Holding\ Cost = \frac{Q}{2} \times H \quad (4)$$

The total inventory cost from 2019 to 2021 which were calculated using the EOQ's method, consecutively, were IDR 198,255,000, IDR 170,265,000 and IDR 239,980,000. It was found that the total inventory cost produced by the EOQ method was smaller than that by the company's method for each year of historical demand data. The differences between the two methods in each year shown in table 2.

Table 2. Comparison between Total Inventory Cost from Company's Method with EOQ's method

Period	Company TIC (IDR)	EOQ TIC (IDR)	Efficiency (IDR)	Efficiency (%)
2019	244.000.000	198.255.000	45.745.000	19
2020	194.000.000	170.265.000	23.735.000	12
2021	338.000.000	239.980.000	98.020.000	29

The efficiency are 19%, 12% and 29%, consecutively, or IDR 45,745,000, IDR 23,735,000 and IDR 98,020,000, respectively. These results indicated that implementation of the EOQ method in the company can reduce the total inventory cost. Based on these results, this research can be continued to the next stage.

Artificial Neural Network Demand Forecasting

Forecasting is one way to estimate market demands which require low-cost resources [23]. In addition, this forecasting stage was intended to fulfill requirements for implementation of the EOQ method, which was to investigate market demands for polyester yarn products in bales in the future, which was in 2022. Forecasting using artificial neural networks was conducted as it can predict demands for the next several period [24].

Data Processing

This forecasting stage was initiated with data preparation, which was data pre-processing as well as training data and target data designing. Data preprocessing was carried out to improve the quality of forecasting, including replacing the anomaly data with its average value. The data pre-processing carried out in this study was to replace data from April to September in 2020 with the average value from January to March and October to December in 2020.

After that, the next stage was normalizing historical demand production data. Data normalization is the process of transforming data into a scale with a certain range and is carried out to simplify the calculation process. One of the ranges of values used, which is between 0 to 1, means that the value 0 is the minimum data or Lower Limit (LL) and the value 1 is the maximum data or Upper Limit (UL). This process is carried out based on the needs or activation functions used in the ANN model. In this study, each data was transformed using Equation (5).

$$X' = \frac{(X - X_{min})}{(X_{max} - X_{min})} \times (UL - LL) + LL \quad (5)$$

Where:
X' = Transformed data
X = Data real
X_{max} = Highest data
X_{min} = Lowest data

In designing a data pattern, the data used for the artificial neural network training process was demand historical data for 2019 and 2020, while the data used for the artificial neural network testing process was demand historical data for 2020 and 2021 [25]–[27].

Design ANN Architecture

There were 4 networks created in this stage, with different training functions. The artificial neural network architecture consists of a backpropagation algorithm, 1 hidden layer, 100 neurons, and binary sigmoid activation function. Binary sigmoid is used as an activation function, because it can meet the requirements in using the backpropagation method, which is easily differentiated, continuous, and the function does not descend. Meanwhile, the training functions involved were *TrainCGB*, *TrainGDX*, *TrainGD*, and *TrainLM* [28], [29]. All parameter of each network used their default values.

Train and Test Each Network

Network training is carried out until the MSE performance is below 0.0001. In addition, the regression value is also considered to get a regression value close to 1. After that, each network is tested using test data consisting of input data and target data.

Error Measuring by Mean Square Error

To find out the test results that are close to the target data, it is done by measuring the error value. The measurement of the error value, usually uses the Mean Square Error (MSE). The test that produces the smallest MSE value is the selected test result [30], [31]. MSE is the square of the mean error. MSE can be calculated using the formula presented in Equation (6).

$$MSE = \frac{\sum (Y_i - \hat{Y}_i)^2}{N} \quad (6)$$

Where:
Y_i = data real
$\hat{Y}_i$ = forecast data
N = number of data

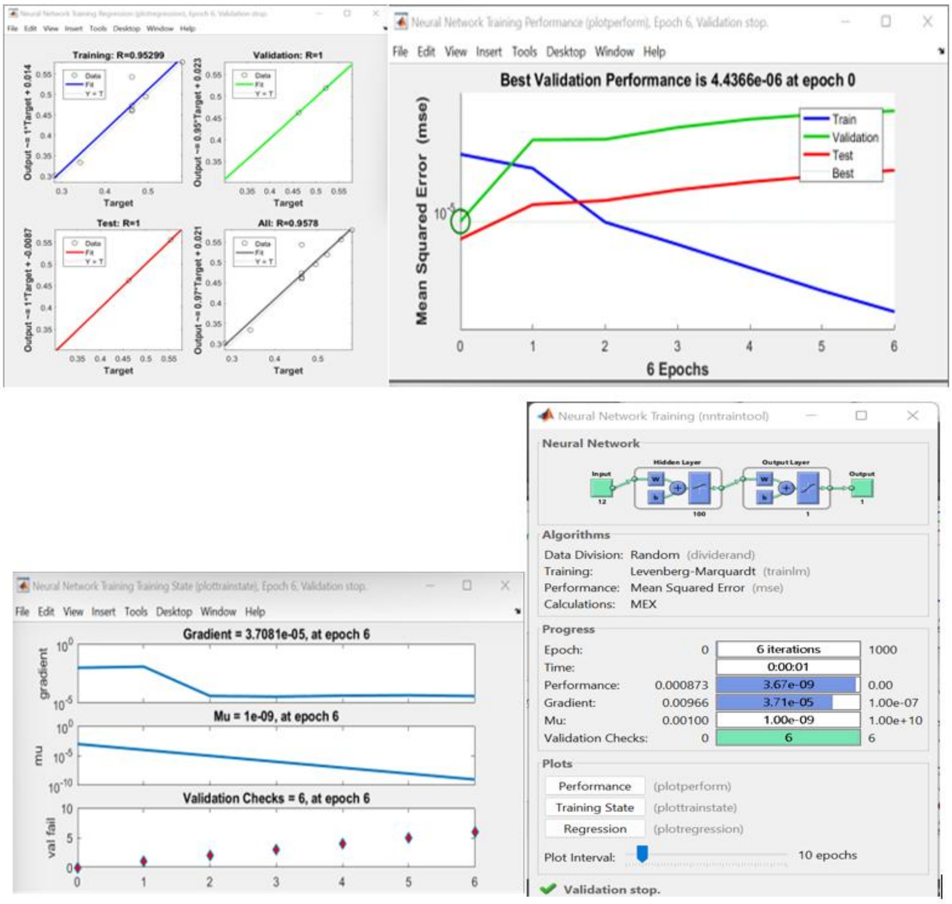

Figure 2. *TrainLM* Visualization

The network that produces the smallest MSE value was the network with the *TrainLM* training function with an MSE value of 0.063528. The network is then saved to be used for forecasting using the Editor Tool feature in the MATLAB software. The result of *TrainLM* network testing is shown in table 3 and the visualized in figure 2.

Table 3. *TrainLM* Testing or Simulation Result

Period	Output	Period	Output
1-21	0.5427	7-21	0.5542
2-21	0.5394	8-21	0.5772
3-21	0.5737	9-21	0.5746
4-21	0.5701	10-21	0.5756
5-21	0.5714	11-21	0.5511
6-21	0.4237	12-21	0.5777

Demand forecasting using MATLAB Editor Tool

The forecasting or simulation stage utilizes the editor tool in MATLAB software as an interface for conducting simulations. Forecasting is carried out to predict production demand for the period of January to December 2022. The first step is to create a variable in the Window Workspace named '*input_forecast*'. Then enter the output of the *TrainLM* network test. Next, the Editor Tool declares variables named '*min_data*' and '*max_data*' and assigns these variables to the minimum and maximum values of historical data. Then initiate the forecasting stage, by creating a variable named '*hasil_prediksi_norm*'. These variables are assigned to the sim function (simulation) and enter the *TrainLM* network and '*input_forecast*' variables into the sim function as shown in figure 3.

```
hasil_prediksi_norm = sim(TRAINLM, input_forecast); %januari 2022
```

Figure 3. Initiative simulation stage

From the simulation results, it will produce forecasts in January 2022. Then to shorten the forecasting time, the next forecast is carried out using the for syntax to loop at the forecasting stage and enter the previous forecasting results into the new '*input_forecast*' variable used in the sim function. Figure 4 is the code used to loop the simulation stage.

```
for n = 1:11
    input_forecast = [input_forecast(end-10:end); hasil_prediksi_norm(end)];
    hasil_prediksi_norm = [hasil_prediksi_norm, sim(TRAINLM, input_forecast)];
end
```

Figure 4. Initiative simulation stage

Furthermore, the syntax will produce forecasting data that is stored in the '*hasil_prediksi_norm'* variable as much as 12 data. Then the next step is to denormalize the '*hasil_prediksi_norm'* variable by using the code as presented in figure 5.

```
%melakukan denormalisasi terhadap hasil prediksi normalisasi
hasil_prediksi_asli = round(hasil_prediksi_norm*(max_data-min_data)+min_data);
%persamaan interpolasi linear
```

Figure 5. Denormalization ANN forecasting result code

Thus, the forecasting stage in this research has been completed. Table 4 is a recapitulation of the results of forecasting that have been denormalized and used for the next stage of this research.

Table 4. Result of denormalization of ANN forecasting results

Forecasting period	Demand Forecast (*Bale*)
1	1.121
2	1.112
3	1.111
4	1.154
5	1.137
6	1.118
7	1.095
8	1.116
9	1.141
10	1.139
11	1.133
12	1.121

Forecasting the demand for polyester yarn production in bale units that has been carried out resulted in a total raw material requirement of 2,510,628 kg, for the year of 2022.

Calculate Economic Order Quantity and Total Inventory Cost Based on Forecasting Result

The calculated economic order quantity value was set for 2022. Based on 2,510,628 kg of total raw material requirement for 2022, the determined EOQ value was 44,817 kg. Based on these results, it can be seen that the frequency of raw material during 2022 is 57 times with a total ordering cost of IDR 114,000,000. Meanwhile, the total storage cost based on the EOQ method was IDR 112,042,500, and the total inventory cost for 2022 was IDR 226,042,500.

Calculate Safety Stock Level and Reorder Point

Calculation of safety stock (*SS*) level and reorder point was intended to carry out an inventory control. In calculating the safety stock level, it is necessary to consider nature of demand and lead time (*LT*), whether they are constant or not. It is known that in this study lead time was constant and demand was not. Therefore, it was necessary to first calculate these factors which were described by an S_{dl} variable. Based on the nature of lead time and demand, the S_{dl} variable was calculated using Equation (7).

$$S_{dl} = Standard\ Deviation \times \sqrt{Lead\ time} \quad (7)$$

Furthermore, the safety stock can be calculated using Equation (8).

$$Safety\ Stock = Sdl \times Z \quad (8)$$

According to results of monthly demand forecasting that had been carried out for the 2022 period, a standard deviation of 2,905 kg was obtained. The lead time for ordering raw materials was 2 days, and therefore the resultant value of S_{dl} variable was 4,109 kg. Furthermore, the service level of the company was obtained at 98%. This value was obtained from the production department of this industry. This value was then used to determine a Z value for calculating the safety stock. Based on the S_{dl} variable value of 4,109 kg, and the *Z* value of 2.05, the safety stock level was obtained at 8,438 kg. In calculating the reorder point, it was necessary to investigate the average daily raw material requirements, in addition to investigating the safety stock level. Reorder point calculated using Equation (9).

$$ROP = (LT \times D) + SS \quad (9)$$

If the total working days is 240 days during 2022, then the average daily raw material requirement is 10,461 kg. In addition, total raw material required or demand (*D*) is 2,510,628 kg. Thus, it can be seen that the reorder point during 2022 was 29,360 kg.

CONCLUSION

Implementation of The EOQ Method based on historical demand data from 2019 to 2021 resulted in a lower total inventory cost than that from the company's method. The resultant efficiencies for each year were 19%, 12%, and 29%, or IDR 45,745,000, IDR 23,735,000, and IDR 98.020,000, respectively. Based on ANN training and testing, a network that produced the smallest MSE value was the one using the *TrainLM* training function with an MSE value of 0.063528. This allows network and network output to be used to forecast demands in 2022. Forecasting was carried out using the Editor Tool feature in the MATLAB 2016 software and produced a total raw material requirement of 2,510,628 kg for synthetic cotton in 2022. Based on demand forecasting in 2022, a 2022 EOQ value was calculated and determined at 44,817 kg with a total inventory cost of IDR 226,042,500. Following the data collection, with a service level of 98% and order lead time of 2 days, a safety stock and reorder point set for 2022 were 8,438 kg and 29,360 kg.

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