Optimization of Production Planning Using Goal Programming and Inventory Control Based On Demand Forecasting Using Neural Networks On CV Bahyu Perkasa

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ABSTRACT

CV Bahyu Perkasa is a company engaged in the concrete construction industry. One of the products produced is paving block. The number of fluctuating demands makes the company decide to stockpile products and procure raw materials regularly to meet consumer demand. This was Born in over-production and overstock. Therefore, a consumer demand forecasting method is needed so that it can minimize production costs and maximize profits. In addition, inventory control methods are needed to reduce storage costs and ordering costs for raw materials. The method used for demand forecasting is an artificial neural network with an MSE error accuracy rate of 0.017769. Forecasting results are used to optimize production planning using goal programming and inventory control planning using MRP. The results of the goal programming optimization model with priority determination produce an optimal solution in fulfilling consumer demand and minimizing production costs of Rp. 99,205,774.00.

CCS CONCEPTS

• Applied Computing ~ Operations Research ~ Industry and Manufacturing • Applied Computing ~ Operations Research ~ Forecasting

KEYWORDS

Optimization, Production Planning, Forecasting, Artificial Neural Network, Goal Programming

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1 Introduction

CV Bayu Perkasa is a company engaged in concrete construction. The production process applied by the company uses two methods: make to stock and make to order. Products made with make-to-stock are products with a high enough demand, while products made with make-to-order are products with unique specifications from consumers, and the number of requests is low [1].

The paving block is one of CV Bayu Perkasa's products which is produced with a make-to-stock system because the number of requests is relatively high. However, the pandemic conditions in 2020 resulted in a drastic decline in demand. Table 1 shows sales number of Paving block TP6 250.

Table 1. Sales number of Paving Block TP6 250

Month	Years		
	2019	2020	2021
Jan	2324	2853	1795
Feb	941	1686	195
Mar	1586	1729	1442
Apr	985	90	1075
Mei	1451	570	1015
Jun	794	1587	0
Jul	1043	285	664
Agu	1896	1213	1551
Sep	1173	1107	1238
Oct	780	0	1560
Nov	901	1086	1015
Des	2252	1347	1852
Total	16126	13553	13402

The pandemic condition has occurred in Indonesia since March 2020. From Table 1, it can be seen that there has been decreased number of requests for paving blocks from 2019 to 2021. Even though the company is aware of the declining demand, the company cannot stop production activities because of the need to pay workers. Workers at CV Bayu Perkasa are paid according to the products produced, so if the company does not carry out the production process, the workers will not get wages. Table 2 shows CV Bayu Perkasa's Production and Sales Data in 2020.

Table 2. Production and Sales Data Comparison 2020

Month	Production of Paving Block TP6 250 (mtr/pcs)	Sales of Paving Block TP6 250 (mtr/pcs)	Inventory
1	3281	2853	428
2	3790	1686	2532
3	3465	1729	4268
4	1096	90	5274
5	519	570	5223
6	1267	1587	4903
7	1230	285	5848
8	0	1213	4635
9	1351	1107	4879
10	941	0	5820
11	0	1086	4734
12	0	1347	3387
Total	16940	13553	

Table 2 shows that in the 8th, 11th, and 12th months, the total production of paving blocks is 0. This is because there were other projects being worked on by CV Bayu Perkasa. CV Bayu Perkasa's problem is that the company does not yet have a strategic methodology to determine the number of products that need to be produced in the future, especially for products produced with a make-to-stock system. This resulted in product accumulation, especially during the pandemic, reaching 3387 meter/pcs.

Therefore, it is necessary to forecast the number of requests using the Artificial Neural Network (ANN) method. Modeling with mathematical methods such as ANN can optimize resources because their needs have been predicted previously **[2]**. ANN is a method that can use to make predictions with non-linear and complex data **[3]**. ANN has proven to be an efficient classification and predictive accuracy without prior system knowledge **[4]**. The ANN method can also be used for relatively small data conditions **[5]**. ANN predicts by exploring the relationship between variables to understand very complex structures, both linear and non-linear data, in a relatively short time **[6]**. The ANN method was used in this study because of the fluctuating number of requests for CV Bayu Perkasa and relatively few data. The artificial network method can learn from the data and is non-linear to identify the model's structure, and is effective in connecting input-output simulations with fluctuating and relatively little data **[7]**. According to Rosmala Sari and A. Sudiarso, ANN can predict aggregate product groups more accurately than traditional demand forecasting. Then aggregate planning is carried out from the forecasting results to produce stock arrangements much better than the initial conditions **[8]**.

The results of demand forecasting using ANN become data for optimizing production planning using the goal programming method. Goal programming (GP) is a method that can solve linear programming problems with more than one goal **[9]**. GP has been widely used as a multi-objective decision-making tool in past decades: in logistics, environmental studies, manufacturing, and economics **[10]**. GP can use several weighting criteria (Akbari, Jones, & Arabikhan, 2021). Several types of GP are distinguished in the weighting of the objective function, including Weighted Goal Programming (WGP), Lexicographic Goal Programming (LGP), and Minmax Goal Programming (Minmax GP) **[11]**. One of the uses of Linear Goal Programming has been to find solutions in the petroleum industry that have many goals **[12]**. GP can provide unwanted deviation variables and combine several objective functions **[13]**. Programming Objectives are used in the research at CV Bayu Perkasa because they have four functions: meeting demand, utilizing regular working hours, dealing with working hours, and production costs. Each objective function has different boundaries and priority scales.

2 Research Methodology

The research process begins with a literature study and field study to identify problems in the system. After finding the problem, then determine the objective research and determine the method of solving the problem. The method used in this study consists of 2 stages, namely: the demand forecasting process using the Artificial Neural Network (ANN) method and optimizing production planning using goal programming. Figure 1 explain the methodology of the research carried out.

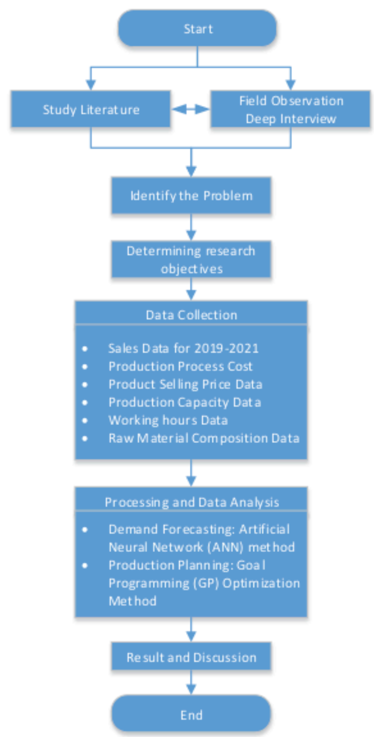

Figure 1. Research Methodology

3 Data Collection and Analysis

3.1 Demand Forecasting with Artificial Neural Network (ANN)
Forecasting is one of the methods commonly used to help organizations with capacity planning, goal setting, and anomaly detection **[14]**. Demand forecasting makes it easier for companies to determine the amount of production that needs to be done in the future and helps determine the amount of raw materials that need to be prepared in the production process **[15, 16]**. The method used in forecasting demand in this paper is artificial neural network (ANN). This is due to the fluctuating characteristics of the company's demand. The predicted product will only focus on Paving Block TP6 250 products as the product that has the highest demand and is a top priority for the company. Figure 2 shows the fluctuating number of requests for Paving Block TP6 250 in 2019 to 2021.

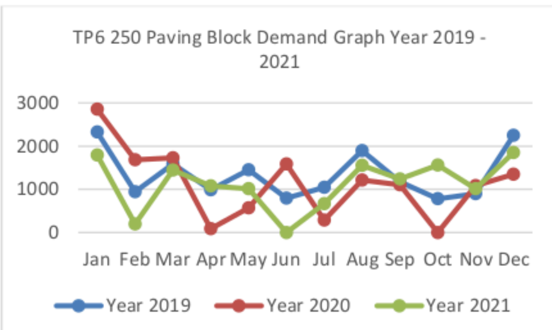

Figure 2. number of requests for Paving Block TP6 250 in 2019 to 2021

Plotting the demand listed in Figure 2, it is known that the data pattern is obtained randomly and does not form a certain trend, such as: seasonality, or others. Artificial neural networks that are deep learning can provide predictive output from stationary data and the linearity is not met **[17]**. Determination of the best network architecture is obtained from the training process and data testing. The data is divided into two, namely training and testing data. Preprocessing and data normalization is the first step before conducting the data training and testing process. Normalization functions to use the sigmoid activation function (binary), where the data must be transformed first because the output range of the sigmoid activation function is [0,1] **[18]**. Table 3 is the normalized TP6 250 Paving Block demand data.

Table 3. Demand Normalization Data

Number of data	Normalization data	Number of data	Normalization data	Number of data	Normalization data
1	0.751665	**13**	0.9	**25**	0.60333
2	0.363863	**14**	0.572766	**26**	0.154679
3	0.544725	**15**	0.584823	**27**	0.504346
4	0.3762	**16**	0.125237	**28**	0.401437
5	0.50687	**17**	0.259832	**29**	0.384613
6	0.322643	**18**	0.545005	**30**	0.1

Table 3. Demand Normalization Data

Number of data	Normalization data	Number of data	Normalization data	Number of data	Normalization data
7	0.392464	**19**	0.179916	**31**	0.28619
8	0.631651	**20**	0.440133	**32**	0.534911
9	0.428917	**21**	0.41041	**33**	0.447143
10	0.318717	**22**	0.1	**34**	0.537434
11	0.352646	**23**	0.404522	**35**	0.384613
12	0.731476	**24**	0.477708	**36**	0.619313

The artificial neural network architecture used in this study is a multi-layer network model with backpropagation and predetermined parameters, namely levenberg-marquardt (trainlm), with epoch 1000 with network model 12-32-10-1 and activation function [logsig, logsig , purelin]. The target MSE value is 0.00001. The data in table 3 is divided into 3 groups, training data, testing data, and output data. The input for training data is data number 1-12 (demand data for 2019), and the results will be compared with data number 13-24 (data demand for 2020). The training data input is data number 13-24, and the results will be compared with data number 25-36 (demand data for 2021). While the output data input is data numbers 25-36, and the result is a demand forecast for 2022.

The results of the training process with the 12-32-10-1 network are shown in Figure 3, which produces an MSE value of 2.9114^{e-}.The output of ANN at the training stage produces a good level of prediction accuracy. The training process aims to make the artificial neural network reach convergence and understand the network pattern from the parameters and algorithms that have been determined.

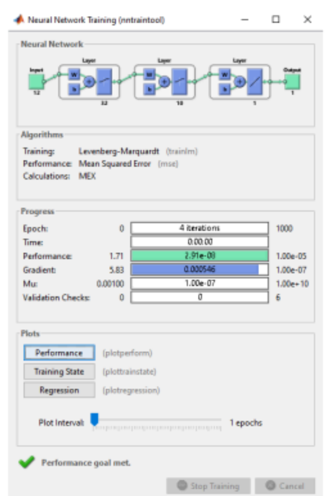

Figure 3. Network Training Results 12-32-10-1

The testing process requires a weight calculation, namely the calculation of the weight of the input to the layer, the calculation of the weight of the layer to the output, the calculation of the bias weight to the layer, and the calculation of the bias weight to the output layer. The testing process by calculating weights and biases to get test results with an MSE of 0.017769 which is quite accurate.

The results of the ANN output in the testing process with initial weight and bias calculations, also produce demand forecasting for the period January 2022 to December 2022. The results of the demand forecasting that have been denormalized can be seen in table 4.

Table 4. Results of demand forecasting with the ANN method

Prediction Results Using ANN Method 12-32-10-1		
Period	Result Prediction	Denormalization Prediction
Jan-22	0.4769024	1392
Feb-22	0.272643162	686
Mar-22	0.424894043	1212
Apr-22	0.458526551	1328
May-22	0.344087869	933
Jun-22	0.464351997	1348
Jul-22	0.28976909	745
Aug-22	0.434675981	1246
Sep-22	0.214041042	484
Oct-22	0.408974241	1157
Nov-22	0.564908187	1696
Dec-22	0.292814266	756

Table 4 is the result of prediction demand forecasting from the ANN method. Table 4 is the result of prediction demand forecasting from the ANN method. These results become input for the production planning process. The limitation of demand data for other types of paving is overcome by using data on the proportion of requests for each paving from 2020-2021. The various types and quantities of requests and their proportions are shown in Table 5.

Table 5. Demand Proportion for each type of paving block

The number of Paving Request 2020-2021				
Paving Block TP6 250 (X1)	Paving Block TP6 350 (X2)	Paving Block TP8 250 (X3)	Paving Block TP8 350 (X4)	Paving Block Exagon (X5)
26955	2654	4491	110	872
Demand Proportion				
76.83%	7.57%	12.80%	0.31%	2.49%

3.2 Production Planning with Goal Programming (GP)

The goal programming model is used for complex problems that can solve more than 1 objective function with optimal solution results that the linear programming model cannot solve [19]. This study uses four objective functions in order of priority as follows, namely: fulfillment of demand, utilization of regular working hours, minimizing the number of overtime hours, and maximizing profits. So that the objective function is formed as follows:

$$Min\ Z = \sum_{i=1}^{5}\left(d_i^- + d_i^+\right) + d_6^+ + d_7^+ + d_8^+ + \sum_{i=9}^{12} d_i^+ \quad (3)$$

Determination of the decision variables is needed to determine the decision variables clearly for the unknown variables to proceed to the modeling stage [20]. The following decision variables are used in the CV Bahyu Perkasa goal programming optimization model below:

X1 = Product decision variable for paving block TP6 250
X2 = Product decision variable for paving TP6 350
X3 = Product decision variable for paving TP8 250
X4 = Product decision variable for paving TP8 350
X5 = Product decision variable for paving Exagon
d_1^- = Variable deviation under paving block request TP6 250
d_1^+ = Variable deviation upper paving block request TP6 250
d_2^- = Variable deviation under paving block request TP6 350
d_2^+ = Variable deviation upper paving block request TP6 350
d_3^- = Variable deviation under paving block request TP8 250
d_3^+ = Variable deviation upper paving block request TP8 250
d_4^- = Variable deviation under paving block request TP8 350
d_4^+ = Variable deviation upper paving block request TP8 350
d_5^- = Variable deviation under paving block request exagon
d_5^+ = Variable deviation upper paving block request exagon
d_6^- = Variable deviation under regular working hours
d_6^+ = Variable deviation upper regular working hours
d_7^- = Variable deviation under overtime hours
d_7^+ = Variable deviation upper overtime hours
d_8^- = Variable deviation below production cost
d_8^+ = Variable deviation above production cost
d_9^- = Variable deviation under the use of cement raw materials
d_9^+ = Variable deviation upper the use of cement raw materials
d_{10}^- = Variable deviation under the use of sand raw materials
d_{10}^+ = Variable deviation upper the use of sand raw materials
d_{11}^- = Variable deviation under the use of screening stone raw materials
d_{11}^+ = Variable deviation upper the use of screening stone raw materials
d_{12}^- = Variable deviation under the use of rock ash raw material
d_{12}^+ = Variable deviation upper the use of rock ash raw material

The fulfillment of each objective function has constraints built into a system's boundaries. The constraint function and each objective function are described as follows.

3.2.1 Request constraint function

The demand constraint function is created by adjusting the results of the demand forecast every month.

Constraint Function:

$$x_1 + d_1^- - d_1^+ = a_{1k} \quad (1)$$
$$x_2 + d_2^- - d_2^+ = a_{2k} \quad (2)$$
$$x_3 + d_3^- - d_3^+ = a_{3k} \quad (3)$$
$$x_4 + d_4^- - d_4^+ = a_{4k} \quad (4)$$
$$x_5 + d_5^- - d_5^+ = a_{5k} \quad (5)$$

Objective Function :

$$Min\ Z = \sum_{i=1}^{5}\left(d_i^- + d_i^+\right) \quad (6)$$

When :
d_i^- = Variable deviation under the paving block type request
d_i^+ = Variable deviation above the paving block type requesti
a_{ik} = Number of requests for the type of paving block
i = Types of paving block products (i = 1, 2, …5)

3.2.2 Regular working hours constraint function

The availability of working hours as a constraint function is used to see the relationship between production time and the number of products produced. The formulation used to formulate this constraint function is as follows :

$$\sum_{i=1}^{5} A_i X_i \leq \sum_{j=1}^{12} JK_j \quad (7)$$

When :
A = Time required to produce 1 m/pcs paving block
X = Decision variables for the type of paving block product
JK = Number of available regular working hours
i = Types of paving block products (i = 1, 2, …5)
j = Month (1, 2,…. 12)

3.2.3 Overtime Constraint Function

The speed for producing all types of products, 1 m/pcs paving block, is the same, with 4 minutes of processing time required. If the demand is high, the company holds an overtime policy with maximum overtime of 20 working days in 1 month with a working time of 5 hours. Therefore, the maximum overtime allowed by the company every month is 100 hours, equivalent to 6000 minutes.

$$d_6^{+} + d_7^{-} - d_7^{+} = JL \quad (8)$$

$$d_6^{+} + d_7^{-} - d_7^{+} = 6000 \quad (9)$$

When :
d_7^{-} = Variable deviation under overtime hours
d_7^{+} = Variable deviation upper overtime hours
JL = Maximum capacity of overtime hours

The objective function is minimize overtime (d_7^{+}) :

$$Min\ Z = d_7^{+} \quad (10)$$

3.2.4 Production cost constraint function

Production costs are costs used in the production process. These costs consist of raw material, labor, and overhead costs. Overhead costs are costs the company must incur outside the operational costs of production. The total production cost for the tp6 250 paving block is Rp. 43,016.00 per m/pcs of paving blocks produced, as well as the production of other types of paving blocks. The company has a limit that the capital issued is Rp. 150,000,000.00 per month. So the constraint function is designed as follows:

$$43016X_1 + 48516X_2 + 45216X_3 + 50716X_4 + 43016X_5 \leq 150000000 \quad (11)$$

$$43016X_1 + 48516X_2 + 45216X_3 + 50716X_4 + 43016X_5 + d_8^{-} - d_8^{+} = 150000000 \quad (12)$$

Objective Function :

$$Min\ Z = d_8^{+} \quad (13)$$

3.2.5 Raw material constraint function

The amount of raw material used for each product must be less than or equal to the availability of these raw materials. The formulation of the formula used is as follows:

$$\sum_{l=1}^{4} \sum_{i=1}^{5} B_l X_i \leq BT_{il} \quad (14)$$

When :
B = The amount of raw material used for each type of paving
x = The decision variable for the paving block type
BT = Amount of raw material availability
i = The type of Paving Block
l = The type of material (l = 1, 2, … 4)
B_1 = Amount of cement raw material usage
B_2 = Amount of sand raw material usage
B_3 = Amount of screening stone raw material usage
B_4 = Amount of use of stone ash raw materials

So, the formula for the constraint function of the use of raw materials to produce 1 m/pcs paving block every month is:

Cement (Kg)

$$18X_1 + 22X_2 + 20X_3 + 24X_4 + 18X_5 \leq 128000 \quad (15)$$

Sand (m³)

$$0.0475X_1 + 0.0475X_2 + 0.0475X_3 + 0.0475X_4 + 0.0475X_5 \leq 840 \quad (16)$$

Screening stone (m³)

$$0.022X_1 + 0.022X_2 + 0.022X_3 + 0.022X_4 + 0.022X_5 \leq 840 \quad (17)$$

Stone ash (m³)

$$0.0273X_1 + 0.0273X_2 + 0.0273X_3 + 0.0273X_4 + 0.0273X_5 \leq 644 \quad (18)$$

Constrain :

$$18X_1 + 22X_2 + 20X_3 + 24X_4 + 18X_5 + d_9^{-} - d_9^{+} = 128000 \quad (19)$$

$$0.0475X_1 + 0.0475X_2 + 0.0475X_3 + 0.0475X_4 + 0.0475X_5 + d_{10}^{-} - d_{10}^{+} = 840 \quad (20)$$

$$0.022X_1 + 0.022X_2 + 0.022X_3 + 0.022X_4 + 0.022X_5 + d_{11}^{-} - d_{11}^{+} = 840 \quad (21)$$

$$0.0273X_1 + 0.0273X_2 + 0.0273X_3 + 0.0273X_4 + 0.0273X_5 + d_{12}^{-} - d_{12}^{+} = 644 \quad (22)$$

Objective Function :

$$Min\ Z = \sum_{i=9}^{12} d_i^{+} \quad (23)$$

1.2.6 Goal Programming Modeling Results

Production planning using LINGO is carried out in a monthly period. As a result, all objective functions are achieved. In addition, production costs in January also decreased by Rp. 50,780.680 from the monthly capital of Rp. 150,000,000.00 determined by the company. So the calculation of the production planning resulted in a total cost reduction of Rp. 992,057,740.00 from Rp. 1,800,000,000.00 or equivalent to a 55.11% decrease in production costs.

In the model results obtained, there is still a large surplus of raw materials, and regular working and overtime hours have not been used. The company can modify the model if it wants to maximize its working hours to be more productive by adding existing restrictions.

4 Conclusion and Recommendation

The results that can be concluded from this study are as follow**:**

1. Forecasting results using the Artificial Neural Network method provide an MSE error value accuracy rate of 0.017769 for Paving Block TP6 250 products in the upcoming 2022 period. The results of monthly demand forecasting in 2022 are in Table 4. The result of the ANN forecasting method can be continued for the following years.

2. The results of optimization of production planning using goal programming with LINGO show that all objective functions can be fulfilled. The four objective functions are the fulfillment of demand with the right quantity, the goal of normal working time, minimizing overtime hours, and minimizing production costs. Based on the calculation of the optimization of production planning using goal programming, there is a decrease in production costs in 1 year of Rp. 992,057,740.00 from the company's capital of Rp. 150,000,000.00 per month or equivalent to 55.11%. The formulation of the mathematical model that has been made can solve the same problem in the following periods. Production planning using the optimization method with goal programming is more useful and produces optimal solutions than production planning for the company's current condition.

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