A Comparison of Forecasting Building Material Inventory between Backpropagation Neural Network And Arima

I A Soenandi\textsuperscript{1} and C Hayat\textsuperscript{2}

\textsuperscript{1}Department of Industrial Engineering Faculty of Engineering & Computer Science Krida Wacana Christian University, Tanjung Duren Raya No. 4 Jakarta 11470, Indonesia

\textsuperscript{2}Department of Information System Faculty of Engineering & Computer Science, Krida Wacana Christian University Tanjung Duren Raya No. 4 Jakarta 11470, Indonesia

\textsuperscript{1}iwan.as@ukrida.ac.id

Abstract. The demand for forecasting task is very important to determine the number of stocks efficiently. This process should accommodate the demand for a company's product or service and control the inventory level. Especially for products such as building materials that needed capitals to buy and wide space to keep it safe. This research has objective to minimize the excessive amount of product in inventory and minimize loss in sales. This study was compared between a method named Back Propagation Neural Network (BPNN) that known as one of the most accurate and widely used forecasting model and ARIMA as a time series model to find the most accurate in forecasting of inventory. In this case, the model of BPNN used 6 input neurons as a monthly period of sale, the price of the product, amount of historical selling, an approximation of project renovation, an approximation of new project building and number of a competitor. And for Arima method we have three trials of tentative models. To compare the accuracy between them, we used the performance criteria such as MAD, MAE, RMSE, RRSE and RAE. In this research, we obtained that forecasting with BPNN is more accurate than ARIMA with error prediction of 19.6, 19.6, 30.4, 0.6, 0.5 for those performance criteria consecutively.

Keywords: inventory; forecasting; building material; backpropagation neural network; Arima;

1. Introduction
The demand forecasting is a critical task to improve the efficiency of a supply chain system [1]. Since each part in the supply chain will process the order in response to the demand signal, the accuracy of demand forecasts will significantly improve the production scheduling, capacity planning, and material requirement planning and inventory management [2]. A qualitative method, time series method, and causal method are 3 important forecasting techniques. Qualitative methods are based on the opinion of subject matter expert and are therefore subjective. Time series methods forecast the future demand based on historical data. Causal methods are based on the assumption that demand forecasting is based on certain factors and explore the correlation between these factors. This prediction of forecast predicts the company sales at any time horizon. Overall, the price of goods becomes a major reference in determining inventory.
For building material inventory, the price of goods affects the effectiveness of venture capital management, while for consumer price the goods become benchmark and adjustment in purchasing the building materials needed.

In the previous literature, many articles stated that the ability to forecast of the future based on past data is a key tool to support individual and organizational decision making. In particular, the goal of Time Series Forecasting (TSF) is to predict the behavior of complex systems by looking only at past patterns of the same phenomenon [3]. Nowadays, forecasting is an integral part of supply chain management and traditional forecasting methods suffer from serious limitations which affect the forecasting accuracy. New methods such as neural network algorithms have been found to be useful techniques for demand forecasting due to their ability to accommodate non-linear data, to capture subtle functional relationships among empirical data, even where the underlying relationships are unknown or hard to describe[4][5]. Recently, the implementation for inventory forecasting is a method that was named back propagation neural networks (BPNNs) have been extensively studied and used in time series forecasting presented a recent review in this area [6]. The major advantage of this method is their flexible nonlinear modeling capability. With BPNNs, there is no need to specify a particular model form.

In this study, we compared the BPNN method with another forecasting method that one of the most important and widely used time series models is the Autoregressive Integrated Moving Average (ARIMA). The popularity of the ARIMA model is due to its statistical properties as well as the well-known Box–Jenkins methodology [7]. In the model building process. ARIMA model is user-friendly in practice and sensitive to the trend of time series data. Its high accuracy of prediction earns the fame as one of best models in time series and highly demand of data abundances for training [8].

This paper presents a time series approach for determining building material stocks amount. We used a comparative approach for modeling the prediction. First, we modeled the forecasting using standard ARIMA [9] models. Then we used nonlinear neural network model trained with “BFGS quasi-Newton Method” based on Back-propagation [10] for modeling the clone evolution series.

We also proposed a forecasting techniques that are suitable to predict the amount of procurement of material supplies accurately. This chosen forecasting method to be used as a supportive qualitative decision, which provides the additional possibility of accommodate certainty demand and minimizes inventory that has a good impact on business sustainability.

2. Methods

2.1. Forecasting with Backpropagation Neural Network
Back Propagation (BP) is a supervised learning algorithm and it often used to train the perceptron. The neural network model which is trained using the BP algorithm is referred to as BPNN [11]. This study has applied the standard procedure of back-propagation neural network as 3 phases. Phase one: Forward Propagation Each Input Unit receives the signal and passes it to the hidden unit on it. In phase two: Backpropagation. This phase has 2 steps. First: count of factor units output based on an error of unit output. Next, we count of hidden factor unit based on an error in hidden units. In phase 3: Putting all the values together and calculating the updated weight value. Next, update of line weights to hidden units. Then this algorithm is done.

The network architecture used in this research was the multi-layer network. In this network, other than the input and output units, there can be one or more other units called the hidden layer which is determined in the training data. The multi-layer neural network can solve the more complex problems compared to the single layer one, although it sometimes requires the more complex and longer training process. The design of artificial neural network architecture was made by determining the numbers of input layer neurons, hidden layer neurons, and output layer neurons.

The dataset was built with several steps. First, we collected data using a questionnaire and interview with several managers of building material shops based on correlation level of procurement and several variables. Those variables are a monthly period of sale (X1), the price of the product (X2), amount of historical selling (X3), an approximation of project renovation (X4), an approximation of new project
building (X5) and a number of a competitor (X6). By analyzing all those variables we want to determine the amount of inventory stock (Y) as shown in Figure 1.

**Figure 1.** A forecasting model for BPNN

### 2.2. Forecasting with ARIMA

Autoregressive integrated moving average model (ARIMA [12]) is capable of identifying complex patterns in temporal dataset and thus widely applied for short-term forecasts. The ARIMA model consists of three basic steps, namely identification, assessment and testing, and diagnostic examination. Furthermore, the ARIMA model can be used for forecasting if the model obtained is sufficient. It should be noted that most periodic sequences are non-stationary and that AR and MA aspects of the ARIMA model are only related to stationary periodic sequences. Stationary means having no growth or decline in the data. The data must roughly be horizontal along the time axis. In other words, the fluctuation of the data around a constant average value is independent of the time and variance of the fluctuation which essentially remains constant at all times.

A non-stationary time series must be converted into stationary data by performing differencing. Differencing is to calculate the change or the difference in the value of observation. The difference value obtained is checked further whether it is stationary or not. If it is not stationary, then there will be another differencing performed. If the variance is not stationary, then there will be a transformation of the algorithm.

In this study, we applied ARIMA for testing variable in time series is inventory level. It’s necessary to accommodate the stationary of variants, it should be noted that most periodicals are non-stationary and aspects AR and MA aspects of the ARIMA model are only relevant to periodic series of stations.
Distrust means no growth or decrease in data. Non-stationary time series must be converted to stationary data by making a difference. To find the best model to use in this forecasting problem we stated several options. We were modeled ARIMA as conducted a trial against the tentatively model (1-1-0 or 0-1-1 or 1-1-1),

3. Result and discussion

3.1. Data normalization

(i) As a first step, to define the best of architectural network, the data was divided into two sections. The two sections of data are: trained and tested data. Totally, we get 22 data from shop managers than we divided two groups of data as trained data 15 value and the rest of 7 data using the testing, this total of data gathering is concerned as our limitation of this research.

(ii) After we collected all the data that related to inventory of this building material, we need to normalize the data as from data input (X1, X2, X3,... Xn) and the output (Y) with formula from Jain et.al [13].

\[ x' = \frac{0.8(x-b)}{(a-b)} + 0.1 \]  

Which:
X' = normalized data; X = existing data; a = maximum data; b = minimum data

The secondary datasets were collected from shop managers and showed in Table 1.

**Table 1. A sample of secondary data from shops managers**

|        | X1    | X2    | X3    | X4    | X5    | X6    | Y   |
|--------|-------|-------|-------|-------|-------|-------|-----|
| Feb 2015 | 80.000 | 25    | 8     | 1     | 18    | 50    |
| Mar 2015  | 80.000 | 42    | 14    | 2     | 18    | 20    |
| Apr 2015   | 85.000 | 128   | 2     | 5     | 18    | 100   |
| Aug 2016   | 83.000 | 53    | 3     | 1     | 19    | 50    |
| Sep 2016   | 83.000 | 16    | 2     | 0     | 19    | 50    |
| Oct 2016   | 83.000 | 131   | 5     | 3     | 19    | 100   |
| Nov 2016   | 83.000 | 27    | 8     | 1     | 19    | 50    |

(iii) The data for input and target after normalized with formula in Equation 1 were shown in Table 2.

**Table 2. A sample of normalization of data input and target**

|   | X1    | X2    | X3    | X4    | X5    | X6    | Y   |
|---|-------|-------|-------|-------|-------|-------|-----|
| 0.17 | 0.10  | 0.17  | 0.40  | 0.26  | 0.50  | 0.23 |
| 0.25 | 0.10  | 0.23  | 0.70  | 0.42  | 0.90  | 0.10 |
| 0.32 | 0.90  | 0.53  | 0.10  | 0.90  | 0.90  | 0.46 |
| 0.39 | 0.90  | 0.18  | 0.60  | 0.26  | 0.90  | 0.23 |
| 0.46 | 0.26  | 0.27  | 0.90  | 0.42  | 0.90  | 0.23 |
| 0.54 | 0.26  | 0.40  | 0.55  | 0.58  | 0.90  | 0.23 |
| 0.61 | 0.26  | 0.19  | 0.15  | 0.26  | 0.90  | 0.23 |
| 0.68 | 0.26  | 0.23  | 0.35  | 0.26  | 0.85  | 0.23 |
| 0.75 | 0.26  | 0.10  | 0.15  | 0.10  | 0.85  | 0.23 |
| 0.83 | 0.42  | 0.26  | 0.45  | 0.26  | 0.85  | 0.23 |
| 0.90 | 0.42  | 0.90  | 0.15  | 0.42  | 0.90  | 0.90 |
The data training is a confirmation of the network model, which is doing multiple times of the attempt that count error to get the best network by determining the number of neurons manually. And this step finally obtained the best network with the smallest errors.

| o  | hl | Neuron | lr  | mc  | Activation Function | MSE   |
|----|----|--------|-----|-----|---------------------|-------|
| 1  | 1  | 5-1    | 0.1 | 0.95| logsig-purelin      | 0.00403|
| 2  | 1  | 6-1    | 0.1 | 0.95| logsig-purelin      | 0.00160|
| 3  | 1  | 7-1    | 0.1 | 0.95| logsig-purelin      | 0.00170|
| 4  | 1  | 8-1    | 0.1 | 0.95| logsig-purelin      | 0.00125|
| 5  | 1  | 10-1   | 0.1 | 0.95| logsig-purelin      | 0.00099|

In Table 3 we showed each MSE in training for 10 neurons and 1 hidden layer has the smallest MSE as 0.00099. Based on those result, we can define the best of architecture for neural network in this research are 6-10-1 it means has 6 inputs, 10 hidden layer neurons, and 1 output that represent the level of inventory.

Next, we used several of trained parameters which selected to find an optimal result as learning rate, constant momentum, Epoch, and Goal. In this research, we obtained best training performance is 0.00099057 with 265 epochs. All these results showed in Figure 2.

**Figure 2.** Graphics of network performance

**Figure 3.** Graphics of trained data regression

This test is done by using the best architectural designs obtained from training, which uses a network structure that consisting of a layer with 6 input neurons. The first hidden layer consists of 10 neurons and the output layer consists of 1 neuron. For the activation function is sigmoid binary (logsig) function and identity function (purelin).

In Figure 3 shows the regression number is 0.98498 which means between the real variables and BPNN on the test has a good correlation. The correlation size shows a good level of equality between the relevant variable variables i.e.: a monthly period of sale, the price of product, amount of historical selling, an approximation of project renovation, an approximation of new project building and number of competitors.

### 3.2 Autocorrelation and Partial Autocorrelation

It should be noted that most periodic sequences are non-stationary and that AR and MA aspects of the ARIMA model are only related to stationary periodic sequences. Stationary means having no growth or decline in the data. A non-stationary time series must be converted into stationary data by performing
differencing. A scaled sequence is said to be stationary or showing a random error if the autocorrelation coefficient for all lags, the numbers are shown at each interval, are statistically not different from zero or different from zero for just several lags ahead. An autocorrelation coefficient is said to be not different from zero if it is in the interval. There was a Lambda (Rounded Value) = -0.5 obtained in the stationary step.

The autocorrelation coefficient for all lag, i.e. the figures shown at each interval is statistically no different from zero or different from zero to just a little lag behind. The autocorrelation coefficient is said to be no different from zero if in interval. At Stationery step to the various results obtained by Lambda (round values) = -0.5.

![Figure 4. Plot graphics of previous stationary data](image1)

![Figure 5. Plot graphics of stationary data after transformation](image2)

A data was said to be stationary for the variety as shown in Figure 4 and the mean, if the rounded value or lambda is worth = 1, then the existing data must be transformed first so that the Lambda value becomes optimal, by the formula: X' = X - 2, or multiplied by 1 / λ.

**TABLE 4.** List of sample stationary data after transformation

| Month      | Inventory | Trans1   |
|------------|-----------|----------|
| January 2016 | 100       | 0.1      |
| February 2016 | 50        | 0.141421 |
| March 2016   | 50        | 0.141421 |
| April 2016   | 50        | 0.141421 |
| May 2016     | 50        | 0.141421 |
| June 2016    | 200       | 0.070711 |
| July 2016    | 100       | 0.1      |
| Augustus 2016| 50        | 0.141421 |
| September 2016| 50       | 0.141421 |
| October 2016 | 100       | 0.1      |
| November 2016| 50        | 0.141421 |

The results obtained from the initial data are still stationary as shown in Table 4, therefore must perform the initial data transformation, to accommodate the stationary of means in step to find stationary
of the means, it is not acceptable if the amount of Lag is more than 3 [14] and the result of transformation data was shown in Figure 5.

From the result that showed in graph Autocorrelation and Partial correlation using MINITAB 17 there is no lag outside the confident interval that means the data was stationary and no need differencing process. Then we have three trials of tentative models and for the third Arima 1-1-1 that means order p = 1, d = 1 and order q = 1 has significant parameters that be obtained. Finally, we obtained the comparison of forecast result from BPNN and ARIMA in period May 2016 until November 2016 as shown in Table 5.

**Table 5. Forecasting comparison with BPNN and Arima**

| Month         | Target (Qty) | Forecast BPNN (Qty) | ARIMA(Qty) |
|---------------|--------------|---------------------|------------|
| May 2016      | 50           | 60.5                | 49.732     |
| June 2016     | 200          | 134.94              | 101,153    |
| July 2016     | 100          | 55.93               | 24.79      |
| August 2016   | 50           | 62.71               | 49.228     |
| September 2016| 50           | 51.61               | 49.594     |
| October 2016  | 100          | 100.68              | 109.533    |
| November 2016 | 50           | 52.57               | 50.322     |

We followed the method of performance criteria measurement for forecasting model from Tay and Cao [15] and Lu.et.al [16]. We evaluated and used respectively mean absolute difference (MAD), mean absolute error (MAE), root mean square error (RMSE), root relative squared error (RRSE), and relative absolute error (RAE). All these results were listed in Table 6.

**Table 6. Error prediction result of BPNN and Arima**

|         | MAD  | MAE  | RMSE | RRSE | RAE  |
|---------|------|------|------|------|------|
| BPNN    | 19.6 | 19.6 | 30.4 | 0.6  | 0.5  |
| ARIMA   | 26.5 | 26.5 | 47.0 | 0.9  | 0.6  |

In improving the efficiency of the supply chain system, there is a need for demand forecasting because each stakeholder involved makes a demand order in response to a demand signal. A good demand forecasting is which can have accurate estimation so as to facilitate the operations of the company such as in planning the material needs and inventory management.

This paper presents a time series approach for modeling in the building materials demand forecasting. The approach used is a linear ARIMA model and non-linear BPNN model. The level of accuracy can be concluded into a good category because it shows the data verification between the actual data and BPNN which most of the data do not have significant differences. As discussed with the store manager that final result is expected. This forecast with BPNN will enable the companies to maximize sales and profits, so they can have a good impact on their business continuity.

4. **Conclusion**

Based on our case study, we concluded the back propagation neural network architecture can be used for inventory predictions in the company is a multi-feed forward layer network with 6-10-1 neuronal structures, or 6 input neurons, 10 neurons, and 1 hidden layer. In this study, we defined the six input neurons that consist of: a monthly period of sale, the price of the product, amount of historical selling,
an approximation of project renovation, an approximation of new project building and number of competitor. As an output of neurons is an inventory forecast value. The activation function was used is binary function sigmoid (logsig) and identity function (purelin) and this model was selected for the best forecast by using parameter of learning rate value 0.1 and momentum constant value 0.95. As a limitation, in this research, we only get 30 data.

As accuracy of prediction is concerned, we compared the error of prediction with performance criteria such as MAD, MAE, RMSE, RRSE and RAE. From the experimental result, this research found that the forecasting with BPNN algorithm has more accurate than ARIMA. This research also suggested in predictions that obtained considerable variation in results, this may be due to limited training data variables. It is expected to continue investigations by adding product variant data, as well as adding or converting with variables that may affect the procurement of goods, for example by reviewing the number of building projects or building renovations that are the major factors affecting the sale of building materials.

5. References

[1] Albarune A R B and Habib M M 2015 A study of forecasting practices in supply chain management 4 pp 55-61
[2] Mishra B K, Raghunathan S and Yue X H 2009 Demand forecast sharing in supply chains. Production & Operations Management 18 (2) pp 152-166
[3] Friedman J H 1991 Multivariate adaptive regression splines. The Annals of Statistics 19 (1), pp. 1–141
[4] Chang P C and Wang Y W 2006 Fuzzy Delphi and backpropagation model for sales forecasting in PCB industry. Expert Systems with Applications 30 (4) pp 715–726
[5] Fildes R, Nikolopoulos K, Crone S F, Syntetos A A 2008 Forecasting and operational research: a review. Journal of the Operational Research Society 59 (9) pp 1150–1172
[6] Lican H, Yuhong Z, Xin X and Fan F 2010 Prediction of investment on inventory clearance based on improved BP neural network in Proceedings of the 1st International Conference on Networking and Distributed Computing pp 73–75
[7] Khasel M, Bijari M and Ardali G A R 2009 Improvement of Auto-Regressive Integrated Moving Average models using Fuzzy logic and control. pp 956-967
[8] Mai T, Ghosh B and Wilson S 2012 Multivariate short-term traffic flow forecasting using Bayesian vector autoregressive moving average model. Transportation Research Board 91st Annual Meeting 12 3728
[9] Wu W, Zhang W, Yang Y and Wang Q 2010 Time series analysis for bug number prediction,” in Proc. 2nd Int. Conf. Softw. Eng. Data Mining (SEDM) pp 589-596
[10] Ghosh A and Chakraborty M 2012 Hybrid optimized back propagation learning algorithm for multi-layer perceptron, Int. J. Comput. Appl 60 (13)
[11] Wang X P, Shi Y, Ruan J B and Shang H Y 2010 Study on the inventory forecasting in supply chains based on rough set theory and improved BP neural network. Advances in Intelligent Decision Technologies Smart Innovation, Systems and Technologies 4 pp 215–225
[12] Box G E, Jenkins M and Reinsel G C 1994 Time Series Analysis: Forecasting and Control. 3rd ed. (Englewood Cliffs, NJ: Prentice Hall)
[13] Jain A K, Mao J and Mohaddin K M 1996 Artificial Neural Networks: A Tutorial. IEEE Computer 29 (3) pp 31-44
[14] Wu W, Zhang W, Yang Y and Wang Q 2010 Time series analysis for bug number prediction, in Proc. 2nd Int. Conf. Softw. Eng. Data Mining (SEDM) pp 589-596
[15] Tay F E H and Cao L 2001 Application of support vector machines in financial time series forecasting Omega 29(4) pp 309-317
[16] Lu C J, Lee T S and Chiu C C 2009 Financial time series forecasting using independent component analysis and support vector machine. Decision Support Systems 47(2) pp 115-125