Modelling Prediction Bandwith

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Modeling of Prediction Bandwidth Density with Backpropagation Neural Network (BPNN) Methods

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Abstract. Using computer networks in campus area which is open access will cause some problems at the speed to access the information. The allocation of bandwidth that provided sometimes does not match the needs of the client, so it takes an accurate prediction of bandwidth usage. This research obtained that Neural Network backpropagation modeling can solve the problem. The stages of research conducted the stage of training and testing phase. Data training is traffic data weekly and conducted by feed-forward back method, with max error 0.001, max hidden layer neuron 5000, constant momentum 0.95 and increase ratio 0.1. Before the data train is conducted, the scaling of the input and target values in the range of 0.1-0.9, then resumes the denormalization after the data train to return the data into Kb form. The results obtained from the training process in the form of comparison data, training performance, and regression. Furthermore, data testing, conducted by using a network that has been developed from the previous results. The test results are shown in the form of real data and predictive data using 8 input layers. In the prediction process, the mean square error generated is 0.0031792 which indicates a low error rate, so it can be stated that the resulting modeling has a level of output accuracy in predicting the use of computer network bandwidth is very high.

Keywords: *Prediction, Bandwidth Density, ANN, Backpropagation*

1. Introduction

The use of computer network today has covered almost all aspects of life, no exception in the campus area. The existence of open access computer network with a wireless on-campus area that causes some problem at access speed of information due to limited availability of bandwidth obtained from provider using in a campus network as a case study, referred the concept from Moussas, Daglis, and Kolega [1] is using data from a campus network. This research measure the bandwidth dominance by the activities of downloading or uploading large files or streaming HD video and difficulty in knowing the number of users of computer networks using wireless to be one cause of bandwidth leaks and quotas on the network. Although each server used is given a certain amount of bandwidth, the limited bandwidth must be of good quality. If the provision of bandwidth is greater than the use, then waste will arise, otherwise if the provision of bandwidth is smaller than the use, then the information access for users to be slow and consequently the campus operational becomes hampered.

By looking at the problems above, it is necessary to do modeling to predict the bandwidth usage in the campus area [2]. The implementation of a quantitative model for forecasting or predicting a decision becomes very important. Time-series forecasting is one of the most commonly used quantitative models in which the same variables from past observations are collected and then analyzed to develop a model that assists in decision making. Qiao et al.[3] presented an empirical study of the forecast error on different timescales, showing that the forecast error does not monotonically decrease with smoothing for larger time-scale. Comparing to this previous research, in our approach is very useful when little knowledge is available in the data collection process or when there is no satisfactory explanatory model that connects predictive variables with other variables

The results of several kinds of research in time series forecasts show that the limitations on traditional statistical models that can only accommodate linear data so that a model is developed to be

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able to take into account, nonlinear patterns observed in real problems in a time series. Nonparametric models also cannot significantly improve accuracy. Balman et al. [4] proposed a network reservation framework to provide guaranteed bandwidth. Our forecast model complements these works by providing traffic forecast information using Artificial Neural Network (ANN) is one of the nonparametric nonlinear models, which has proven its accuracy for time series forecasting. We agreed that the backpropagation neural network is one of the most commonly used algorithms on network artificial neural method. The BPNN model can identify the causal relationships of some specific time series of underlying phenomena for various purposes, including forecasting, decisions, and control. Such models can be used for a number of reasons to analyze the dependencies between several other time series at a time, predict future values to support decision making, design simple, and practice control schemes of system output from desired targets.

Another advantage of the ANN method is the ability to perform nonlinear modeling in a time series data with a high degree of accuracy [5]. There are three layers in the network structure which are the input layer, the hidden layer, and the output layer, and the neurons in the input and output layer are respective input variables and output variables. The performance of BPNN is mainly influenced by the number of nodes in each layer and the maximum epoch performed [6]. In this research, BPNN topology used is determined by the trial-and-error method. The main contribution of this article is to predict the bandwidth density of wireless networks on campus using back propagation neural network method where the modeling produced has a high degree of accuracy.

2. Research Method

2.1. Research Flow

The stages of the study are shown in Figure 1 below. First, this study was conducted by pre-processing the data by normalizing the data, then determine the parameters used in this study. After the parameter used has been set, the desired output value and the MSE and epoch constraints were set. The training levels run continuously until you get the desired weight and bias and obtained the minimum error results.

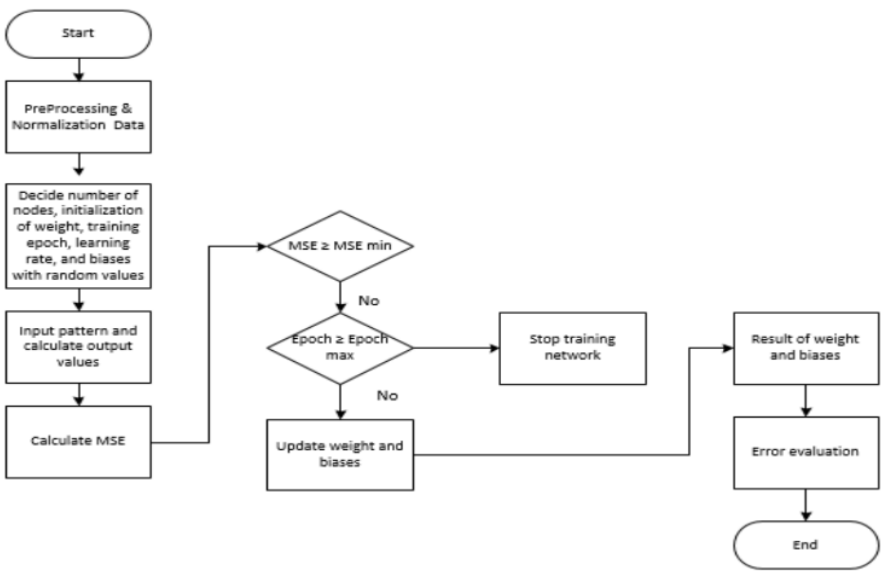

Figure 1. Research Flow

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The stages of the research carried out are shown in Figure 1 below. The study was conducted by preliminary data processing by normalizing the data first. Then, the parameters used in the study were determined. After the parameters used have been set, the desired output value and the MSE and epoch constraints were set. Stages of training are carried out continuously until the desired weight and bias and minimum error results were obtained.

2.2 Histrocial Data and Statistical Properties

The data used is secondary data as in table 1 below, which includes data usage (traffic) taken from the historical data of internet usage in Campus in the Jakarta area in 3 different locations. The data train period used is December data for 2 weeks, and the predicted bandwidth is the data of 2nd week. From the various data obtained above, the data used only total traffic data (volume) at each hour

Table 1. Actual data of internet usage per December 2016

Date Time	Traffic Total (Volume)	Traffic Total (speed)	Traffic in (volume)	Traffic in (speed)	Traffic out (volume)	Traffic out (speed)	Down time	coverage
23/11/2016 12:00:- 13:00	61.432.889 Kb	138.926 kbit/s	56.299.088 Kb	127.317 kbit/s	5.133.802 Kb	11610 kbit/s	0%	100%
23/11/2016 13:00-14:00	61.727.993 Kb	140.484 kbit/s	55.511.014 Kb	126.335 kbit/s	6.216.980 Kb	14149 kbit/s	0%	100%
23/11/2016 14:00-15:00	63.759.510 Kb	145.105 kbit/s	58.279.120 Kb	132.632 kbit/s	5.480.390 Kb	12472 kbit/s	0%	100%
23/11/2016 15:00-16:00	64.055.488 Kb	145.778 kbit/s	59.244.129 Kb	134.829 kbit/s	4.811.358 Kb	10950 kbit/s	0%	100%
23/11/2016 16:00-17:00	51.436.528 Kb	117.061 kbit/s	47.524.702 Kb	108.159 kbit/s	3.911.826 Kb	8903 kbit/s	0%	100%
23/11/2016 17:00-18:00	46.517.869 Kb	105.866 kbit/s	39.755.151 Kb	90.475 kbit/s	6.762.718 Kb	15391 kbit/s	0%	100%
23/11/2016 18:00-19:00	30.762.575 Kb	70.011 kbit/s	29.157.336 Kb	66.358 kbit/s	1.605.239 Kb	3653 kbit/s	0%	100%
23/11/2016 19:00-20:00	21.339.060 Kb	48.565 kbit/s	19.584.125 Kb	44.571 kbit/s	1.754.934 Kb	3994 kbit/s	0%	100%
23/11/2016 20:00-21:00	24.744.853 Kb	56.315 kbit/s	22.821.432 Kb	51.937 kbit/s	1.923.421 Kb	4377 kbit/s	0%	100%
23/11/2016 21:00-22:00	14.458.173 Kb	32.905 kbit/s	13.659.600 Kb	31.087 kbit/s	798.572 Kb	1817 kbit/s	0%	100%

Table 2 below explains the actual data for bandwidth usage in December 2016. The traffic data displayed is a measure of data transfer that has been done every hour throughout the week. Bandwidth itself can be interpreted as the number of data transfer consumption values that are calculated in a matter of bits / second or commonly referred to as bits per second (bps), between the server and client in a certain time

Table 2. Data of Bandwidth Usage December 2016 Period

Time	Actual data per December 2016						
	Monday	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
00.00	1.944.862	1.562.990	2.291.706	2.692.837	3.234.360	281.982	2.019.012

01.00	1.865.804	1.876.172	1.420.433	581.104	1.417.372	321.525	2.320.710
02.00	3.458.240	1.728.435	1.527.009	1.073.526	896.920	525.798	1.442.344
03.00	4.480.933	505.360	1.236.960	706.597	629.663	362.595	349.500
04.00	1.062.546	468.197	807.016	918.060	2.362.664	358.550	1.540.112
05.00	861.873	2.001.913	1.270.385	1.390.753	1.794.131	1.066.366	1.823.404
06.00	4.809.084	8.489.782	8.501.804	11.282.648	7.579.191	3.711.965	1.135.355
07.00	24.340.765	26.505.444	22.493.947	33.632.282	22.539.263	13.089.892	1.057.580
08.00	36.839.356	28.232.085	40.498.422	44.085.829	29.907.463	18.660.445	1.172.106
09.00	45.063.742	33.790.517	45.687.057	44.322.351	42.580.471	30.691.241	2.883.271
10.00	46.549.289	42.225.885	63.525.155	46.473.057	44.938.626	16.172.934	1.066.240
11.00	46.109.632	42.383.837	39.220.516	46.337.352	43.655.779	14.414.736	1.694.356
12.00	44.634.346	44.778.173	38.681.964	44.312.203	30.568.029	18.193.361	1.432.497
13.00	44.293.636	44.681.801	39.186.014	45.280.313	24.687.825	16.788.937	1.982.248
14.00	43.292.248	44.429.773	38.951.276	46.305.572	28.141.230	17.220.856	1.255.039
15.00	39.787.729	41.859.783	38.914.635	45.865.548	23.585.938	12.966.531	1.423.890
16.00	34.757.172	38.405.309	37.846.592	38.927.361	17.728.513	9.479.619	2.335.253
17.00	24.455.187	32.100.948	28.283.094	29.184.904	13.048.068	6.304.035	2.381.663
18.00	23.910.088	22.031.822	31.303.078	24.466.058	7.116.754	4.052.549	2.330.083
19.00	16.363.318	14.531.776	22.795.861	21.294.220	4.900.498	3.157.590	1.794.157
20.00	13.599.784	22.341.951	23.722.077	15.502.650	2.626.198	2.386.518	2.159.072
21.00	6.090.573	7.891.060	7.886.010	9.980.691	2.973.493	3.268.777	2.737.898
22.00	2.710.075	2.928.637	4.081.2215	966.844	2.266.762	2.669.468	3.171.000
23.00	3.027.280	2.713.853	4.658.776	3.367.314	253.333	2.523.089	2.299.693

Table 3 explains the actual data for bandwidth usage after normalization. The purpose of data normalization is to change the measurement scale of the data into another form to meet the analysis assumptions. Before the data used in the training process of artificial neural networks need, it needs to conduct the scaling on input and targets values in the range of 0.1 - 0.9. Scaling is conducted by using the following equation;

$$X' = \frac{0{,}8(x-b)}{(a-b)} + 0{,}1 \quad (1)$$

where : X = data result of normalization
x = original data / initial data
a = maximum value of original data
b = minimum value of original data

Table 3. Data of Bandwidth Usage after Normalization in December 2016 Period

	Actual data per December 2016						
Time	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**	**Sunday**
00.00	0.123877	0.119064	0.128248	0.1211324	0.130657	0.126879	0.110784
01.00	0.12288	0.123011	0.117267	0.119195	0.108575	0.136177	0.119855
02.00	0.14295	0.121149	0.11861	0.145497	0.118011	0.115816	0.120852
03.00	0.15584	0.105734	0.114955	0.146505	0.107019	0.118084	0.1
04.00	0.112756	0.105266	0.109536	0.124285	0.103495	0.121104	0.100743
05.00	0.110227	0.124596	0.115376	0.113219	0.108038	0.118206	0.105097
06.00	0.159976	0.206365	0.206517	0.144176	0.160796	0.126605	0.116393
07.00	0.406142	0.433424	0.382866	0.394481	0.386185	0.241054	0.153238
08.00	0.563667	0.455186	0.609784	0.509295	0.473492	0.459643	0.133176

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09.00	0.667323	0.525241	0.657179	0.596375	0.611454	0.516625	0.147639
10.00	0.686046	0.631556	0.9	0.590936	0.585076	0.553197	0.15412
11.00	0.680505	0.633547	0.593678	0.611146	0.595465	0.488144	0.144726
12.00	0.661911	0.663724	0.58689	0.5896	0.590198	0.486946	0.132122
13.00	0.657617	0.662509	0.593243	0.593345	0.591105	0.39028	0.141945
14.00	0.644996	0.659333	0.590285	0.586514	0.550027	0.364274	0.162583
15.00	0.600827	0.626942	0.589823	0.60325	0.559667	0.362201	0.149433
16.00	0.537425	0.583404	0.576362	0.515104	0.549321	0.297876	0.139839
17.00	0.407584	0.503947	0.455829	0.471578	0.469433	0.232362	0.128225
18.00	0.400714	0.377041	0.493891	0.463771	0.416715	0.224453	0.133797
19.00	0.305599	0.282515	0.386671	0.314021	0.403502	0.132213	0.135466
20.00	0.270769	0.38095	0.398344	0.285351	0.380937	0.131305	0.13608
21.00	0.176127	0.198819	0.198756	0.211897	0.254653	0.125623	0.149603
22.00	0.133521	0.136276	0.150802	0.128962	0.151902	0.109619	0.157616
23.00	0.137519	0.133569	0.158081	0.132414	0.119352	0.108493	0.+135981

After the data is normalized, the data will be trained to form a network that will be used. The data trained is data in the time span of 1 day or 24 hours. Before data is trained, data is formed into a pattern first. There is an input pattern, the first is the input data and the second is the target data.

2.3 Development of a Neural Network

This research used Backpropagation Artificial Neural Network (BPNN) method. BPNN was selected because it is known to be very effective for solving problems which require pattern mapping, i.e. if it is given for an input pattern [7], the generated output will be as the desired. The ANN network architecture used in this research was the multi-layer 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.

Backpropagation algorithm architecture consists of three layers, namely input layer, hidden layer and output layer [8]. At the input layer, there is no computational process, but at the input layer, the X signal input occurs to the hidden layer. In the hidden and output layer, the computation process occurs for weight and bias and the magnitude of the hidden output and output layer is also calculated based on certain activation functions. In this backpropagation algorithm, the binary sigmoid activation function is used, because the expected output is between 0 and 1. The three backpropagation layers are the input layer, hidden layer, and output layer. At the input layer, the input is varied with Xn. At the hidden layer, there are weights (Vij) and bias (Voj), and Z as the hidden layer data. At the output layer, there are weights (Wij) and bias (Woj) with the output data with Y variable [9].

First, as taking input, we initialize the weights, then do the backpropagation process algorithm which consists of advanced computation which aims to track the size of the error and back computing to update and adjust the weights. Updating weights can be done in two ways, namely without momentum and with momentum [10]. However, what is explained below in updating the weight is done without regard to the amount of momentum. Thus, in the backpropagation method, the algorithm that must be performed is weight initialization, feedforward and backpropagation computing and stopping condition initialization based on the error limit value or the number of epoch limits. Epoch is a series of steps in learning ANN. One epoch is defined as one time ANN learning.

Each layer consists of several numbers of neurons based on the specification of the problem designed by the user. Each layer receives input generated from the previous layer and also generates output through the activation function to the next layer in the network. The BPNN model developed in this paper is attached in Figure 2 below:

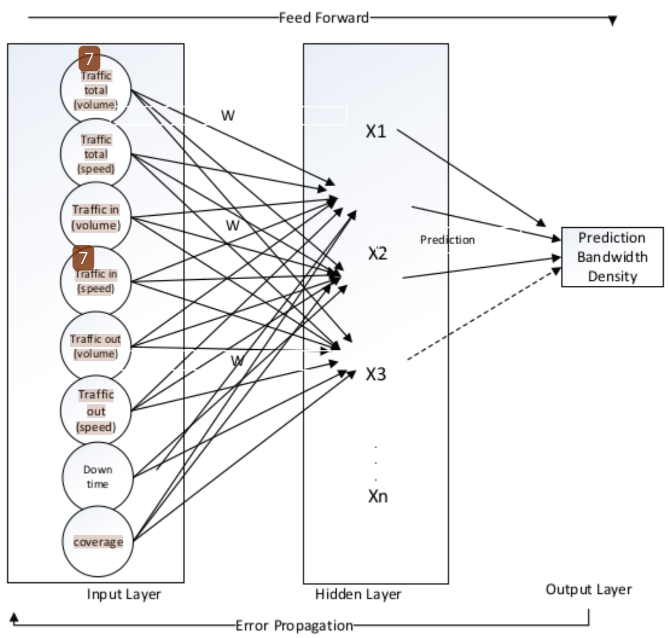

Figure 2. BPNN Model

The proposed BPNN model development procedures are as follows:

Pre-Processing data :	This stage includes the collection of historical data that will be used in training data. Data obtained from interviews and field observations on campus at 3 different locations in the Jakarta. The data obtained then normalized before the determination of parameters such as max error of 0.001 with epoch ranging from 100, 500, 1000, 2500, and 5000 epoch, momentum constant of 0.95 and increase ratio of 0.1.
Training Phase :	The standard training algorithm on BPNN through 3 phases, they are advanced propagation phase, reverse propagation phase, and change of weight and bias phase. The training process is conducted to find the best equation by conducting weight training and can be trial-error. Put the training data is conducted manually by inserting weights one by one which then find the most commonly emerging and most stable equations or having no significant differences.
Testing Phase:	The testing stages are performed using training data that has been previously produced.
Generated output :	The output results are in the form of bandwidth density prediction based on the model that has been produced.

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3 Result Interpretation

3.1 Data Training Process

Data training is conducted after data processing is completed. The data training was conducted using feed-forward back propagation method of error destination of 0.001, maximal 1000 with constant momentum of 0.95 and increase the ratio of 0.1.

After training, the network and training results are obtained. In this prediction process, the prediction result is still in the form of normalization. Therefore, it needs a process of denormalization to restore data into a Kilobyte form.

The denormalization process uses the following equation:

$$X = ((X' - 0{,}1) * \frac{Min*Max}{0{,}8}) + Min \qquad (2)$$

Explanation:
X' = normalization data
X = denormalization data
Min = smallest data of original data
Max = largest data of original data

After the training process, it will produce information in the form of data comparison, training performance, and regression.

Figure 3. Best Training Performance

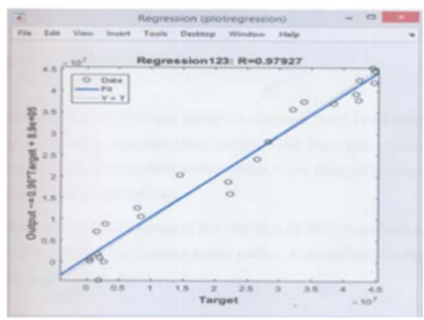

Figure 4. Regression

Figure 3 above shows the best performance at the training stage. The best training performance produced on epoch 989 was 0.0019241. Figure 4 shows the result of the regression value, R = 0.97927.

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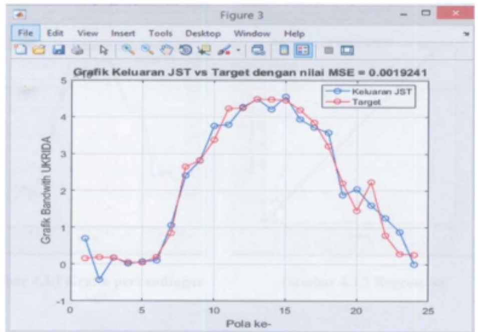

Figure 5. JST vs Target Output graph with MSE value = 0.001924

Figure 5 shows a graph of BPNN output with a predetermined output value target at the training stage

3.2 Data Testing Process

After the training process is done, the next step is to evaluate the performance of the algorithm or commonly called the testing phase. In the testing process, the algorithm performance of the resulting model will be tested using a testing set, in which the testing set and training set are different data. Figure 6 shows a graph of BPNN output with a predetermined output value target at the testing stage

Predicting bandwidth by using BPNN will make it easier to do the prediction process. The prediction process is conducted by using network modeling that has been developed. Once the data is inputted, it will do the prediction process by determining the day that will be predicted.

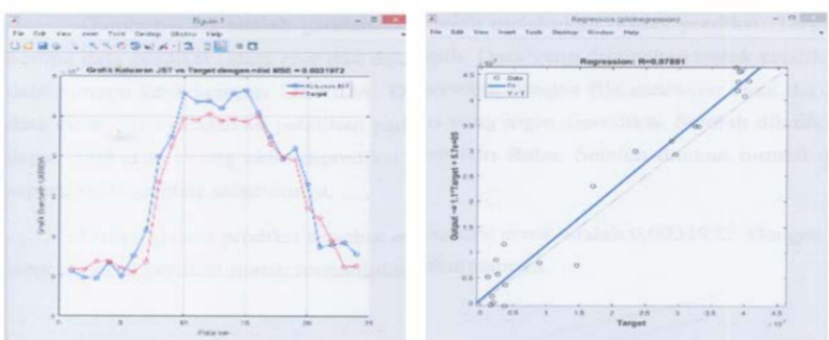

Figure 6. Graph of comparison and regression of test result

The figure above shows a comparison graph between the original data and the predictive data. The blue graph is the graph showing the prediction, while the red graph is the graph showing real data.

In the prediction process, the mean square error is 0.0031792 which indicates a very small error rate. So the results of these predictions show the accuracy.

4 Conclusion

In this research, the BPNN model architecture is consists of 8 input layers as Traffic Total (Volume), Traffic Total (speed), Traffic in (volume), Traffic in (speed), Traffic out (volume), Traffic out (speed), Downtime, and coverage. We conducted this model through 2 stages, namely data training stage and data testing stage. Data training was conducted using feed-forward back propagation method. In the data testing phase, the test performed has a low error rate, seen from the mean square error generated is 0.0031792 which indicates a very small error rate. The low error indicates the predicted bandwidth density is more accurate.

For further development, this research can be done by collecting more data and a longer time span so that the scope of research can be expanded.

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