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Research Article

Analysis and Prediction of Vertical Office Network Bandwidth Using a Backpropagation-Based Neural Network

Muhammad Jamil Asshiddiq [a,1,*]; Iffatul Mardhiyah [a,2]
[a] *Universitas Gunadarma, Jl. Margonda Raya Pondok Cina, Depok and 16424, Indonesia*
[1] *muhjamilasshiddiq@gmail.com;* [2] *iffatul@staff.gunadarma.ac.id*
* *Corresponding author*

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Abstract

The digitalization of business and operational processes in vertical offices has transformed work behaviour, creating a critical need for stable internet connectivity to ensure smooth operations. This issue triggered stakeholders and technical teams to evaluate bandwidth usage trends to enable optimal future planning. Backpropagation, a neural network algorithm, can effectively predict complex patterns using historical data. The ability of the Backpropagation algorithm to adapt to time-series data makes it ideal for forecasting network bandwidth. Therefore, this research aims to analyze and predict network bandwidth requirements using a Backpropagation-Based Neural Network algorithm. This study, which utilized data from October 2022 to September 2024, demonstrates that the Neural Network model provides a high prediction accuracy. The Backpropagation algorithm able to predict the increasing trend in bandwidth usage for October 2024 with a prediction accuracy of 89.08% and a Mean Absolute Percentage Error (MAPE) of 10.92%. Model used in this study can be used as a reference parameter for stakeholders and technical teams within organization for future bandwidth allocation.

Keywords: Network Bandwidth; Prediction; Neural Network; Backpropagation.

Introduction

Internet technology has become an essential component in almost all activities of vertical offices, transforming traditional operational proccess into more efficient digitalized processes. A vertical office refers to an institution with a centralized hierarchical structure, in which decisions are made at the upper level (Regional Office) before being commanded to the lower level (Branch Office) [1]. Examples of digitalized activities are email communication, video conference, and the use of various cloud-based applications to support operational activities [2], [3], [4]. The adoption of digitalized work behaviour has contributed to substantial improvements in operational efficiency within vertical offices. However, this transformation also poses the potential for a growing demand of stable internet connectivity and increased bandwidth capacity, as operational components continue to evolve toward fully digital workflows over time [5], [6], [7].

Bandwidth is a time-series data, as its measurement is conducted continuously over a specific period. Bandwidth data records the extent of network utilization within a given timeframe [8], enabling the analysis of usage patterns based on historical trends. This analysis allows vertical offices to predict potential future network bandwidth requirements, which can serve as a reference for decision-making and as a basis for optimizing network bandwidth capacity planning more efficiently [9], [10].

The Backpropagation-Based Neural Network algorithm is a supervised learning method designed to solve complex tasks such as identification, prediction, and pattern recognition [11], [12], [13]. The predictive capability of the Backpropagation algorithm is developed through a process of learning based on historical data. This process allows the algorithm to identify and internalize complex patterns within the data, thereby enabling it to produce predictive results for future data [14], [15].

The study of electricity consumption forecasting in North Sumatra [16] highlights the increasing demand for electrical energy, requiring accurate predictions to support effective policy-making. Forecasting is crucial for ensuring sufficient supply, as electricity demand is influenced by population growth, customer categories, and regional economic activity. The Backpropagation Neural Network method was applied using six input variables, including

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customer types (household, industrial, business, social), total population, and GRDP of North Sumatra. The optimal network architecture consisted of a hidden layer with three neurons and one output neuron representing electricity consumption in GWh. The forecasting results for 2018 closely aligned with actual data, yielding a low MAPE of 1.037% and MSE values of 0.00405 (training) and 0.00545 (testing). Overall, the Backpropagation algorithm model demonstrated very high accuracy in forecasting regional electricity consumption.

The study of [17] highlights that the use of public computer networks on campus often results in reduced access speed, primarily due to bandwidth allocation that does not align with user requirements. This issue can be addressed using a Backpropagation Neural Network approach, which enables the prediction of bandwidth demand based on weekly time-series data. Such predictions provide valuable support for bandwidth allocation planning and contribute to enhancing overall network performance in campus environments.

This study aims to assist vertical offices in optimizing bandwidth capacity allocation and enhancing overall operational efficiency. The observational data consist of hourly bandwidth utilization records over a 23-month period, from October 2022 to September 2024, to predict utilization data for October 2024. The prediction results are expected to serve as a reference for relevant stakeholders and technical teams in bandwidth allocation planning from service providers, thereby improving cost efficiency in the operational expenses of vertical offices.

Method

A. Research Method

Figure 1 shows the research flow diagram. The study begins with collecting network bandwidth utilization data from the vertical office. The utilization data are real-time records obtained using a bandwidth utilization monitoring application. The second stage involves dataset partitioning, where the dataset consists of 762 data entries divided into two parts: 731 entries for training data and 31 entries for testing data. The dataset represents the combined utilization of both upload and download activities. The third stage is data normalization for both the training and testing datasets. The fourth and fifth stages involve the development of the Neural Network model for bandwidth prediction analysis. The sixth stage is the denormalization process to restore the predicted values to their original scale. The final stage is the analysis of error values, including MAD, RMSE, and the accuracy of the Neural Network model used.

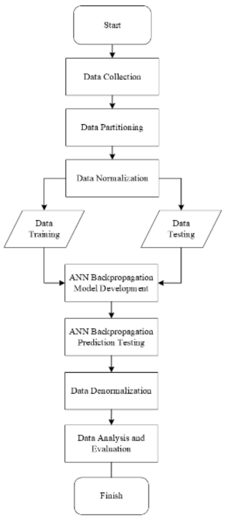


Figure 1. Research Flow Diagram of Bandwidth Prediction

B. Data Normalization

The success of a Neural Network model largely depends on the data quality; therefore, data normalization is a critical process. Data normalization ensures that all attributes within the dataset are on a uniform scale, which can accelerate the training process [18]. Without data normalization, the differences in attribute scales can lead to unstable gradients, thereby slowing the weight update process in the Neural Network model. Furthermore, normalization can prevent attributes with significantly larger values from dominating others, resulting in more balanced weights and reducing the risk of overfitting, as the model and activation functions can focus on relevant patterns while avoiding misleading patterns caused by extreme values [19]. In this study, data normalization was performed using the Min-Max normalization method, which transforms the value range into [0,1] or [-1,1] [20]. The normalization performed using Equation 1 :

$$x' = \frac{0{,}8*(x - x_{min})}{x_{max} - x_{min}} \quad (1)$$

Explaination:
x’ = normalized value
x = value to be normalized
x_min = minimum value of the data attribute
x_max = maximum value of the data attribute

C. Backpropagation Neural Network

The Backpropagation Neural Network consist of three architectural layers: the input layer, which serves as the layer input data; the hidden layer, which processes the input data; and the output layer, which generates the final output based on the processed data from the hidden layer [21], [22]. Each layer plays a crucial role, from mapping input patterns to optimally producing predictive output patterns. **Figure 2** illustrates the architecture of the Backpropagation Neural Network layers.

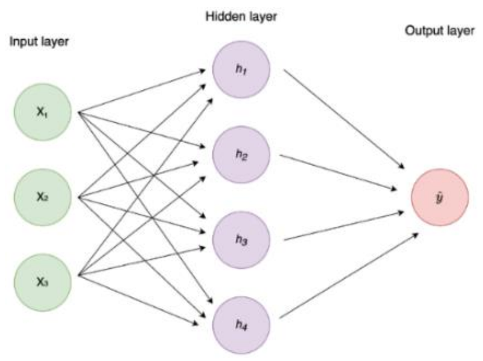


Figure 2. Backpropagation Neural Network Architecture

The activation function plays a key role in the operation of a Backpropagation Neural Network. It determines whether a neuron will be activated based on the received input value [23]. Commonly used activation functions including the sigmoid function, ReLU (Rectified Linear Unit), and tanh. The proper selection of an activation function significantly affects the convergence speed of a Neural Network model and its ability to accurately model nonlinear relationships [24], [25].

D. Data Denormalization

Data denormalization is the process of converting normalized prediction values back to their original scale to more accurately represent the actual bandwidth values [26], [27]. The denormalization performed using Equation 2 :

$$x = \frac{(x' - 0{,}1)(x_{max} - x_{min})}{0{,}8} + x_{min} \quad (2)$$

Explaination:
x’ = normalization value
x = denormalization value
x_{min} = minimum value of the data atribute
x_{max} = maximal value of the data atribute

E. Data Analysis

The final stage of the analysis involves evaluating the performance of the Backpropagation Neural Network model to determine how accurately the predictions reflect the patterns learned from network utilization data. This evaluation is carried out by calculating error metrics such as Error, MSE, MAD, and MAPE, followed by a comparison between the actual data and the predicted data.

a. Error

Error is the difference between the actual data and the predicted data. The error value can be either positive or negative, depending on the relationship between the actual and predicted data [28].

$$Error = Actual\ Data - Predicted\ Data \quad (3)$$

b. Mean Square Error (MSE)

Mean Squared Error (MSE) is the average of the squared differences between the actual values and the predicted values. MSE is used to measure the average squared error, giving greater weight to larger errors. [29], [30].

$$MSE = \sum \frac{(Actual\ Data - Predicted\ Data)^2}{Dataset\ Size} \quad (4)$$

c. Mean Absolute Deviation (MAD)

Mean Absolute Deviation (MAD) is the average of the absolute differences between the actual values and the predicted values. MAD provides a measure of error in the same units as the original data. [30].

$$MAD = \sum \left| \frac{Actual\ Data - Predicted\ Data}{Dataset\ Size} \right| \quad (5)$$

d. Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is the average percentage of the absolute errors between the actual values and the predicted values. MAPE indicates the magnitude of the prediction error in form of percentage values [30], [31]. MAPE indicates the magnitude of prediction error in percentage form.

$$MAPE = \sum \left| \frac{Actual\ Data - Predicted\ Data}{Dataset\ Size} \right| * 100\% \quad (6)$$

e. Prediction Accuracy

Prediction accuracy is the percentage value that indicates how accurately the predictions are produced by the neural network model.

$$Model\ Accuracy = \frac{Actual\ Data - Predicted\ Data}{Actual\ Data} * 100\% \quad (7)$$

$$Model\ Accuracy = 100\% - Error\ Percentage$$

F. Research Object

This study uses bandwidth utilization traffic data from a vertical office as the research object, with hourly recording intervals over a 24-month period from October 2022 to October 2024. The data were obtained from utilization records generated by the Paessler Router Traffic Grapher (PRTG) bandwidth monitoring software, which operates in real time on the IT infrastructure of the vertical office.

Results and Discussion

A. Data and Model Preparation

This stage describes the preparation of the dataset and the neural network model to be used.

a. Data Preparation

The collected data are divided into two parts: training data and testing data, with a split ratio of 96:4. The training dataset consists of 731 data entries, while the testing dataset consists of 31 data entries.

Table 1. Data Training

Date & Time	Upload and Download 00:00 – 23:00 (Kbps)						
	00:00	01:00	02:00	…	21:00	22:00	23:00
01-Oct-22	5,806	5,709	6,714	…	5,831	4,121	5,132
02-Oct-22	5,139	4,895	3,228	…	5,474	9,215	8,344
03-Oct-22	4,297	3,128	3,514	…	20,826	14,047	9,033
04-Oct-22	8,296	5,447	7,831	…	14,446	11,076	9,591
05-Oct-22	7,528	4,918	4,062	…	20,656	9,771	10,568
…	…	…	…	…	…	…	…
26-Sept-24	69,254	204,771	124,114	…	72,697	64,493	67,118

Date & Time	Upload and Download 00:00 – 23:00 (Kbps)						
	00:00	01:00	02:00	…	21:00	22:00	23:00
27-Sept-24	63,826	37,910	40,156	…	43,754	40,112	33,938
28-Sept-24	73,137	59,897	22,808	…	31,370	31,732	27,079
29-Sept-24	37,963	24,921	25,237	…	39,151	29,277	23,105
30-Sept-24	30,064	33,260	25,633	…	35,014	33,421	37,888

Table 2. Data Testing

Date & Time	Upload and Download 00:00 – 23:00 (Kbps)						
	00:00	01:00	02:00	…	21:00	22:00	23:00
01-Oct-24	18,024	19,657	12,960	…	37,606	32,293	15,315
02-Oct-24	14,423	15,615	9,724	…	34,693	28,034	24,087
03-Oct-24	22,737	19,724	14,533	…	34,861	32,689	22,550
04-Oct-24	26,496	17,469	15,840	…	29,918	27,501	21,345
05-Oct-24	21,430	15,452	16,373	…	32,602	12,690	13,016
…	…	…	…	…	…	…	…
27-Oct-24	78,051	31,528	26,328	…	42,089	31,194	27,053
28-Oct-24	25,413	32,279	23,354	…	40,018	35,908	21,642
29-Oct-24	35,918	23,011	15,153	…	62,645	103,376	66,195
30-Oct-24	54,185	40,769	40,008	…	57,228	52,320	35,848
31-Oct-24	47,536	40,308	41,353	…	40,238	37,622	29,655

Table 1 presents the total upload and download bandwidth utilization from October 1, 2022, to September 30, 2024, while Table 2 presents the total upload and download bandwidth utilization from October 1 to 31, 2024. The utilization data are recorded on an hourly basis, with entries from 00:00 to 23:00. The recorded values represent bandwidth utilization in units of kilobits per second (Kbps).

b. Dataset Normalization

The data in Tables 1 and 2 are then normalized to facilitate the training process of the network and to produce more optimal output data.

Table 3. Normalized Training Data

Date &Time	Upload and Download 00:00 – 23:00						
	00:00	01:00	02:00	…	21:00	22:00	23:00
01-Oct-22	0.1618	0.1591	0.1875	…	0.1625	0.1141	0.1427
02-Oct-22	0.2526	0.2368	0.1287	…	0.2743	0.5170	0.4605
03-Oct-22	0.1050	0.1014	0.1026	…	0.1553	0.1347	0.1194
04-Oct-22	0.1106	0.1000	0.1089	…	0.1335	0.1210	0.1154
05-Oct-22	0.1139	0.1034	0.1000	…	0.1664	0.1228	0.1260
…	…	…	…	…	…	…	…
26-Sept-24	0.1755	0.4028	0.2675	…	0.1813	0.1675	0.1719
27-Sept-24	0.1714	0.1095	0.1148	…	0.1234	0.1147	0.1000
28-Sept-24	0.9000	0.7058	0.1617	…	0.2873	0.2926	0.2244
29-Sept-24	0.6802	0.2923	0.3017	…	0.7155	0.4219	0.2383
30-Sept-24	0.1210	0.1259	0.1141	…	0.1287	0.1262	0.1331

Table 4. Normalized Test Data

Date & Time	Upload and Download 00:00 – 23:00						
	00:00	**01:00**	**02:00**	…	**21:00**	**22:00**	**23:00**
01-Oct-24	0.1156	0.1187	0.1060	…	0.1525	0.1425	0.1105
02-Oct-24	0.1100	0.1125	0.1000	…	0.1530	0.1389	0.1305
03-Oct-24	0.1283	0.1221	0.1114	…	0.1532	0.1488	0.1279
04-Oct-24	0.1183	0.1037	0.1011	…	0.1238	0.1199	0.1100
05-Oct-24	0.2255	0.1628	0.1725	…	0.3426	0.1338	0.1373
…	…	…	…	…	…	…	…
27-Oct-24	0.9000	0.2131	0.1363	…	0.3690	0.2082	0.1470
28-Oct-24	0.1153	0.1269	0.1118	…	0.1399	0.1330	0.1089
29-Oct-24	0.1335	0.1127	0.1000	…	0.1767	0.2425	0.1824
30-Oct-24	0.1575	0.1337	0.1323	…	0.1629	0.1542	0.1249
31-Oct-24	0.1371	0.1266	0.1281	…	0.1265	0.1227	0.1112

Tables 3 and 4 present the normalized bandwidth utilization data. Table 3 contains data from October 1, 2022, to September 30, 2024, while Table 4 contains data from October 1 to 31, 2024. The utilization data are recorded hourly, from 00:00 to 23:00, and are represented in decimal values. With a total of 762 rows of data where each row represent hourly data each day, the dataset is labeled to facilitate data identification during the training and testing processes.

Table 5. Data Label

Data Training Time	Data Training Row	Data Training Label	Row Output	Label Data Output	Data Output Time
Oct 1 2022 – 30 Sept 2024	1 – 731	DT01	732	DU01	Oct 1 2024
Oct 2 2022 – 1 Oct 2024	2 – 732	DT02	733	DU02	Oct 2 2024
Oct 3 2022 – 2 Oct 2024	3 – 733	DT03	734	DU03	Oct 3 2024
Oct 4 2022 – 3 Oct 2024	4 – 734	DT04	735	DU04	Oct 4 2024
Oct 5 2022 – 4 Oct 2024	5 – 735	DT05	736	DU05	Oct 5 2024
Oct 6 2022 – 5 Oct 2024	6 – 736	DT06	737	DU06	Oct 6 2024
Oct 7 2022 – 6 Oct 2024	7 – 737	DT07	738	DU07	Oct 7 2024
Oct 8 2022 – 7 Oct 2024	8 – 738	DT08	739	DU08	Oct 8 2024
Oct 9 2022 – 8 Oct 2024	9 – 739	DT09	740	DU09	Oct 9 2024
Oct 10 2022 – 9 Oct 2024	10 – 740	DT10	741	DU10	Oct 10 2024
Oct 11 2022 – 10 Oct 2024	11 – 741	DT11	742	DU11	Oct 11 2024
Oct 12 2022 – 11 Oct 2024	12 – 742	DT12	743	DU12	Oct 12 2024
Oct 13 2022 – 12 Oct 2024	13 – 743	DT13	744	DU13	Oct 13 2024
Oct 14 2022 – 13 Oct 2024	14 – 744	DT14	745	DU14	Oct 14 2024
Oct 15 2022 – 14 Oct 2024	15 – 745	DT15	746	DU15	Oct 15 2024

Data Training Time	Data Training Row	Data Training Label	Row Output	Label Data Output	Data Output Time
Oct 16 2022 – 15 Oct 2024	16 – 746	DT16	747	DU16	Oct 16 2024
Oct 17 2022 – 16 Oct 2024	17 – 747	DT17	748	DU17	Oct 17 2024
Oct 18 2022 – 17 Oct 2024	18 – 748	DT18	749	DU18	Oct 18 2024
Oct 19 2022 – 18 Oct 2024	19 – 749	DT19	750	DU19	Oct 19 2024
Oct 20 2022 – 19 Oct 2024	20 – 750	DT20	751	DU20	Oct 20 2024
Oct 21 2022 – 20 Oct 2024	21 – 751	DT21	752	DU21	Oct 21 2024
Oct 22 2022 – 21 Oct 2024	22 – 752	DT22	753	DU22	Oct 22 2024
Oct 23 2022 – 22 Oct 2024	23 – 753	DT23	754	DU23	Oct 23 2024
Oct 24 2022 – 23 Oct 2024	24 – 754	DT24	755	DU24	Oct 24 2024
Oct 25 2022 – 24 Oct 2024	25 - 755	DT25	756	DU25	Oct 25 2024
Oct 26 2022 – 25 Oct 2024	26 – 756	DT26	757	DU26	Oct 26 2024
Oct 27 2022 – 26 Oct 2024	27 – 757	DT27	758	DU27	Oct 27 2024
Oct 28 2022 – 27 Oct 2024	28 – 758	DT28	759	DU28	Oct 28 2024
Oct 29 2022 – 28 Oct 2024	29 – 759	DT29	760	DU29	Oct 29 2024
Oct 30 2022 – 29 Oct 2024	30 – 760	DT30	761	DU30	Oct 30 2024
Oct 31 2022 – 30 Oct 2024	31 – 761	DT31	762	DU31	Oct 31 2024

Table 5 shows the labeled data. In the first row, the data from October 1, 2022, to September 30, 2024, consist of 731 rows, which serve as the training data and are labeled as DT01. The data from October 1, 2024, represent the test data, corresponding to row 732, and are labeled as DU01. This labeling process continues sequentially until the final data entries, labeled DT31 and DU31.

c. Neural Network Model

In **Figure 3**, the Backpropagation Neural Network architecture, developed using MATLAB, consists of four layers, with the *tansig* activation function applied to both the hidden layers and the output layer. The first layer, the input layer, contains 731 neurons representing the number of input attributes. The second layer, Hidden Layer 1, consists of 365 neurons corresponding to the number of days in a year, while the third layer, Hidden Layer 2, consists of 24 neurons representing the number of hours in a day. Finally, the fourth layer, the output layer, contains a single neuron that produces the predicted output value of the Neural Network model. The developed Neural Network employs the Gradient Descent training method, with a learning rate of 0.25, 6,000 training epochs, and 2,000 validation checks.

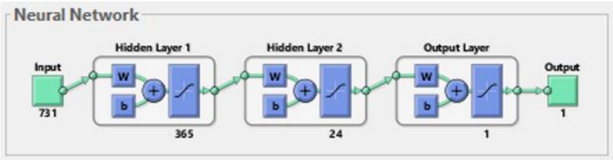


Figure 3. Neural Network Backpropagation Architecture

B. *Neural Network Model Training*

a. Model Training

The next stage involves training and testing the Neural Network model using the prepared dataset. This process is executed in 31 segments, generating 31 output values corresponding to each day in October 2024. The training and testing are conducted using the Neural Network Tool in MATLAB, as illustrated in **Figure 4**.

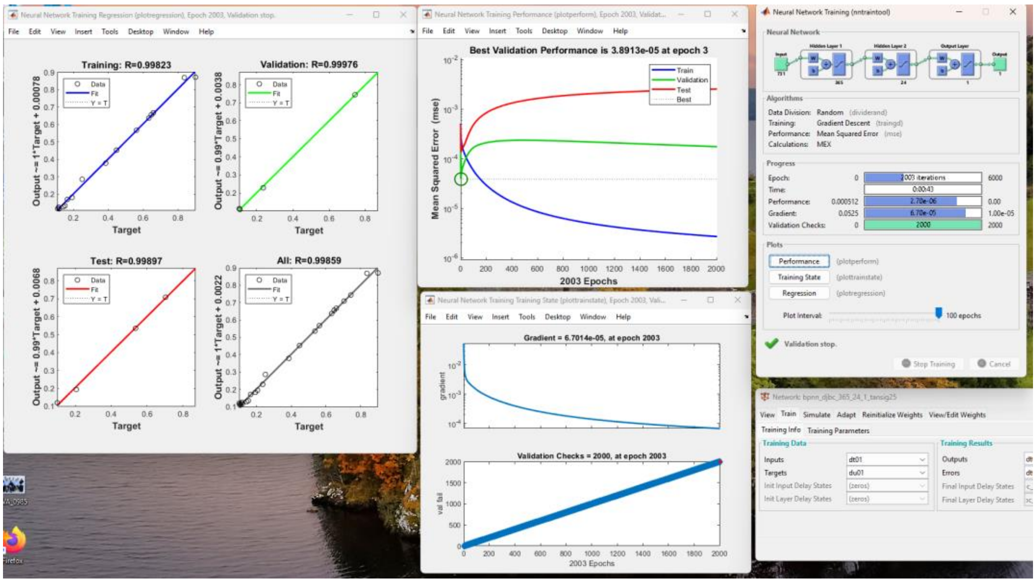


Figure 4. training and testing process for DT01 data and the DU01 output data.

b. Data Testing Result

The results of the 31 training and testing processes are presented in **Table 6**.

Table 6. Data Testing Result

Date & Time	Upload and Download 00:00 – 11:00						
	00:00	01:00	02:00	…	21:00	22:00	23:00
01-Oct-24	0.1163	0.1093	0.1025	…	0.1440	0.1424	0.1089
02-Oct-24	0.1093	0.1113	0.1020	…	0.1504	0.1370	0.1288
03-Oct-24	0.1198	0.1211	0.1182	…	0.1529	0.1264	0.1281
04-Oct-24	0.1099	0.1032	0.1047	…	0.1253	0.1196	0.1139
05-Oct-24	0.1995	0.1635	0.1670	…	0.3434	0.1302	0.1456
…	…	…	…	…	…	…	…
27-Oct-24	0.8433	0.1971	0.1377	…	0.3499	0.2064	0.1422
28-Oct-24	0.1152	0.1298	0.1096	…	0.1425	0.1352	0.1102
29-Oct-24	0.1093	0.1220	0.1180	…	0.1908	0.2338	0.1949
30-Oct-24	0.1290	0.1424	0.1236	…	0.1493	0.1570	0.1759
31-Oct-24	0.1149	0.1053	0.1064	…	0.1266	0.1306	0.1113

C. *Data Denormalization*

Denormalization is the process of restoring the Neural Network model's testing results to their original form after the data has previously undergone normalization. The results of the denormalization data is presented in **Table 7**, which is then further analyzed and validated by comparing the predictions with the actual data.

Table 7. Denormalization of Predicted Data

Date & Time	Upload and Download 00:00 – 11:00						
	00:00	01:00	02:00	…	21:00	22:00	23:00
01-Oct-24	18422	12968	11119	…	33634	32767	14585
02-Oct-24	14110	12926	10671	…	34108	27623	23629
03-Oct-24	18611	15154	18033	…	35290	22120	22971
04-Oct-24	21270	16563	18165	…	31328	27694	24050
05-Oct-24	18950	14019	16641	…	35561	12695	14355
…	…	…	…	…	…	…	…
27-Oct-24	74214	29044	27544	…	48253	34247	27989
28-Oct-24	25358	27269	22197	…	42422	37947	22580
29-Oct-24	20927	23748	26639	…	73096	100536	75750
30-Oct-24	38151	37210	35732	…	50922	55423	66603
31-Oct-24	32184	24361	26478	…	41020	43908	30021

D. Result Comparation

The comparison between the predicted data and the actual data is presented to illustrate the closeness of the model's prediction results to the actual values. The comparison is provided in the form of tables and graphs, which are used to visualize the 31 test data points, each representing a comparison between the predicted results and the actual data. Table 8 presents the prediction comparison data, where the "Actual" column represents the original data and the "Expected" column represents the predicted data.

Table 8. Comparation Table Prediction Data & Actual Data

Data Label	Data	Upload and Download 00:00 – 23:00						
		00:00	01:00	02:00	…	21:00	22:00	23:00
DU1	Actual	18,024	19,657	12,960	…	37,606	32,293	15,315
	Expected	18422	12968	11119	…	33634	32767	14585
DU2	Actual	14,423	15,615	9,724	…	34,693	28,034	24,087
	Expected	14110	12926	10671	…	34108	27623	23629
DU3	Actual	22,737	19,724	14,533	…	34,861	32,689	22,550
	Expected	18611	15154	18033	…	35290	22120	22971
DU4	Actual	26,496	17,469	15,840	..	29,918	27,501	21,345
	Expected	21270	16563	18165	…	31328	27694	24050
DU5	Actual	21,430	15,452	16,373	…	32,602	12,690	13,016
	Expected	18950	14019	16641	..	35561	12695	14355
…	…	…	…	…	…	…	…	…
DU27	Actual	78051	31528	26328	…	42089	31194	27053
	Expected	74214	29044	27544	…	48253	34247	27989
DU28	Actual	25413	32279	23354	…	40018	35908	21642
	Expected	25358	27269	22197	…	42422	37947	22580
DU29	Actual	35918	23011	15153	…	62645	103376	66195
	Expected	20927	23748	26639	…	73096	100536	75750
DU30	Actual	54185	40769	40008	…	57228	52320	35848
	Expected	38151	37210	35732	…	50922	55423	66603
DU31	Actual	47536	40308	41353	…	40238	37622	29655
	Expected	32184	24361	26478	…	41020	43908	30021

The comparison data is visualized in graphical form to facilitate data analysis and interpretation based on data in Table 8. Figures 5 through 35 present comparison graphs of the predicted data (Expected) against the actual data (Actual).

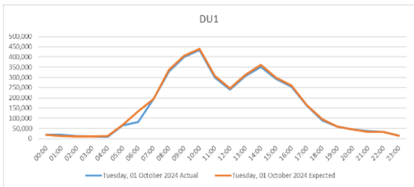


Figure 5. DU1 Graph

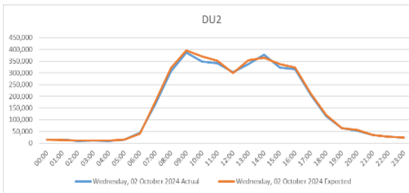


Figure 6. DU2 Graph

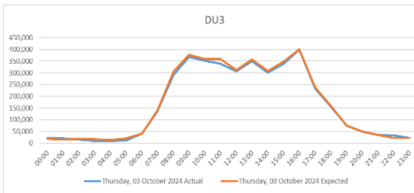


Figure 7. DU3 Graph

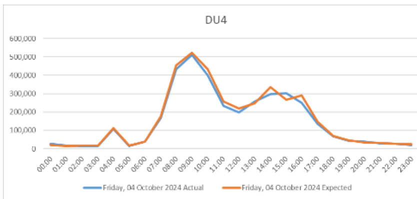


Figure 8. DU4 Graph

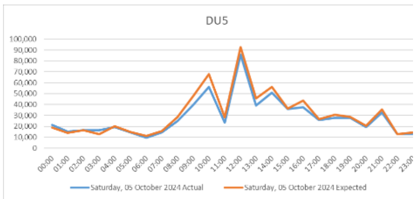


Figure 9. DU5 Graph

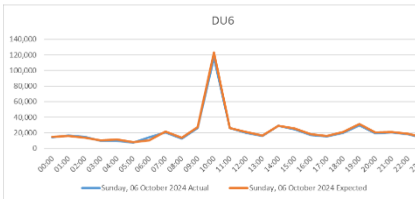


Figure 10. DU6 Graph

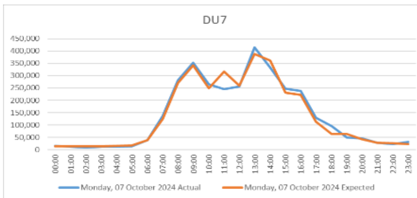


Figure 11. DU7 Graph

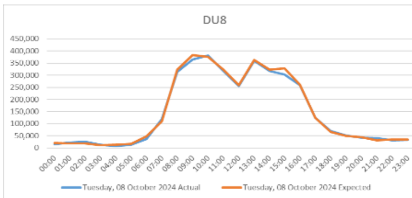


Figure 12. DU8 Graph

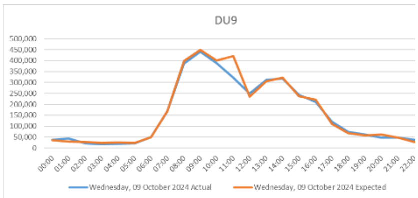


Figure 13. DU9 Graph

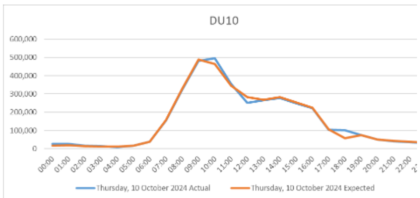


Figure 14. DU10 Graph

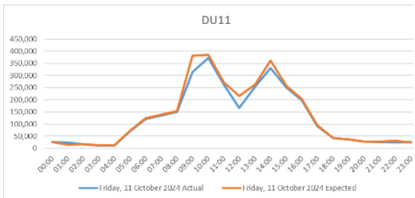


Figure 15. DU11 Graph

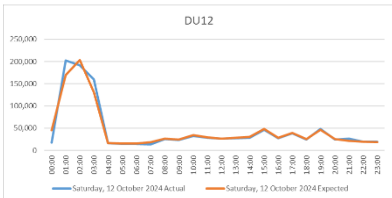


Figure 16. DU12 Graph

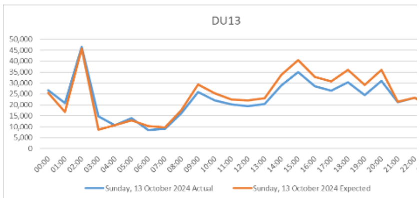


Figure 17. DU13 Graph

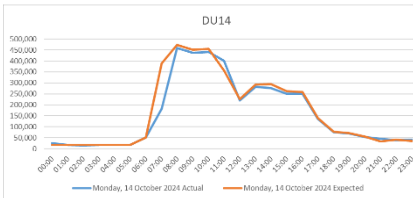


Figure 18. DU14 Graph

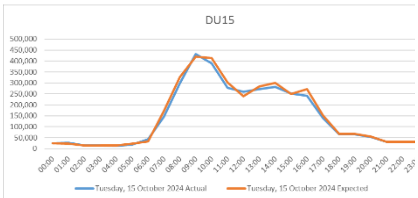


Figure 19. DU15 Graph

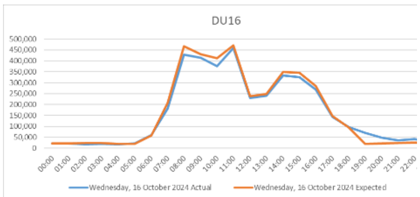


Figure 20. DU16 Graph

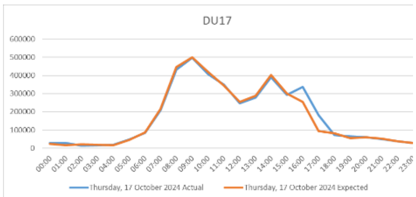


Figure 21. DU17 Graph

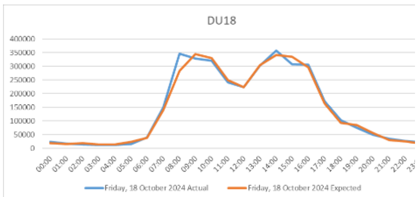
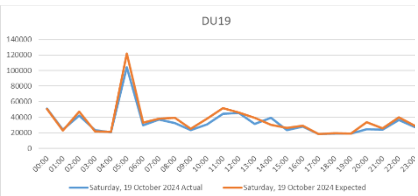
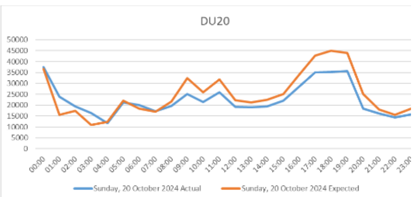


Figure 22. DU18 Graph





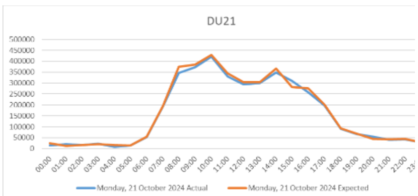
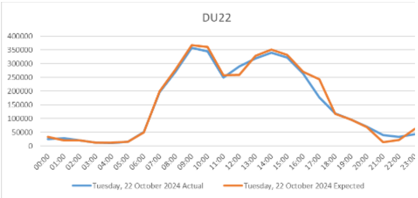
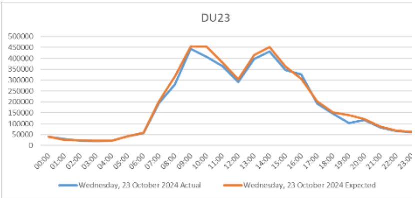


Figure 23. DU19 Graph **Figure 24.** DU20 Graph **Figure 25.** DU21 Graph





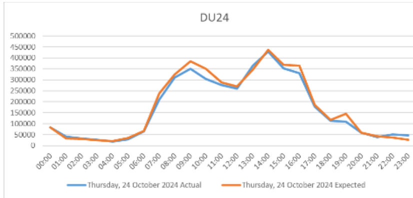
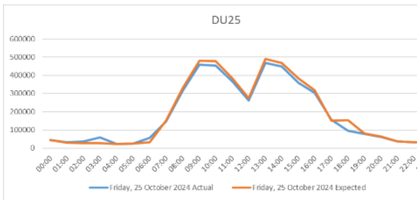
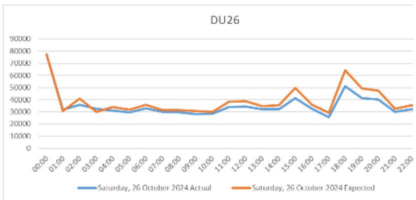


Figure 26. DU22 Graph **Figure 27.** DU23 Graph **Figure 28.** DU24 Graph





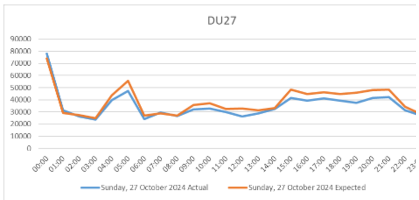
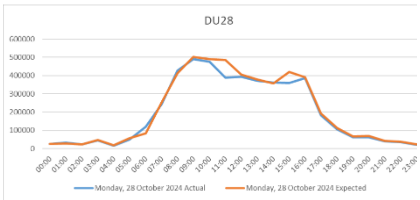
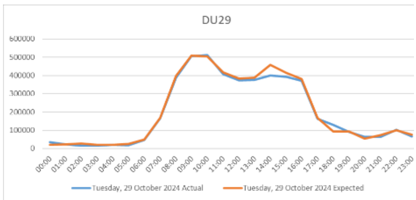


Figure 29. DU25 Graph **Figure 30.** DU26 Graph **Figure 31.** DU27 Graph





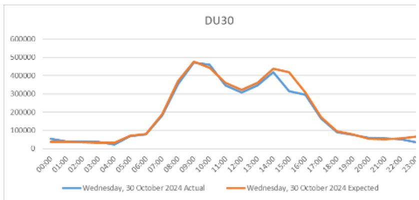


Figure 32. DU28 Graph **Figure 33.** DU29 Graph **Figure 34.** DU30 Graph

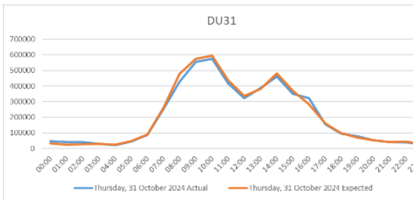


Figure 35. DU31 Graph

The graphical visualizations in **Figures 5** through **35** show that nearly all predicted data closely matches the patterns of the actual data, indicating that the Neural Network model performs predictions accurately.

E. Evaluation

The prediction results are then evaluated to measure how accurately the Neural Network model can predict bandwidth. The evaluation metrics used to assess the model's performance including Error, Mean Absolute Deviation (MAD), Mean Squared Error (MSE), Mean Absolute Percentage Error (MAPE), and overall prediction accuracy.

a. Error

The error between the predicted data and the actual data was calculated to obtain the Error values. These Error values are presented in **Table 9**.

Table 9. Error values

Date & Time	Upload and Download 00:00 – 23:00						
	00:00	01:00	02:00	…	21:00	22:00	23:00
01-Oct-24	-398.1	6689.5	1841.3	…	3972.5	-474.0	729.6
02-Oct-24	313.1	2689.2	-946.9	…	584.6	411.1	458.0
03-Oct-24	4126.0	4569.6	-3499.6	…	-428.5	10569.0	-421.1
04-Oct-24	5225.8	906.1	-2325.4	…	-1410.1	-192.6	-2705.4
05-Oct-24	2479.6	1433.1	-267.6	…	-2958.6	-5.1	-1339.1

Date & Time	Upload and Download 00:00 – 23:00						
	00:00	01:00	02:00	**…**	21:00	22:00	23:00
…	…	…	…	…	…	…	…
27-Oct-24	3837.4	2484.3	-1216.1	…	-6163.8	-3053.0	-935.8
28-Oct-24	54.7	5010.5	1157.3	…	-2404.0	-2038.6	-937.8
29-Oct-24	14991.5	-737.1	-11486.4	…	-10451.4	2840.4	-9555.3
30-Oct-24	16034.4	3559.4	4275.7	…	6306.4	-3103.3	-30755.5
31-Oct-24	15351.6	15946.9	14874.5	…	-782.1	-6285.9	-365.7

b. Mean Absolute Deviation (MAD)

The Error values were then converted into Mean Absolute Deviation (MAD) to measure the magnitude of the absolute deviation between the predicted and actual data. The MAD calculation results are presented in **Table 10**.

Table 10. MAD Calculation Values

Date & Time	Upload and Download 00:00 – 11:00						
	00:00	**01:00**	**02:00**	…	**21:00**	**22:00**	**23:00**
01-Oct-24	398	6689	1841	…	3972	474	730
02-Oct-24	313	2689	947	…	585	411	458
03-Oct-24	4126	4570	3500	…	429	10569	421
04-Oct-24	5226	906	2325	…	1410	193	2705
05-Oct-24	2480	1433	268	…	2959	5	1339
…	…	…	…	…	…	…	…
27-Oct-24	3837	2484	1216	…	6164	3053	936
28-Oct-24	55	5010	1157	…	2404	2039	938
29-Oct-24	14991	737	11486	…	10451	2840	9555
30-Oct-24	16034	3559	4276	…	6306	3103	30755
31-Oct-24	15352	15947	14875	…	782	6286	366

c. Mean Squared Error (MSE)

The MAD values obtained from Table 10 were subsequently used to calculate the Mean Squared Error (MSE), which represents the average of the squared differences between the predicted and actual data. The MSE values are presented in **Table 11**.

Table 11. MSE Values

Date & Time	Upload and Download 00:00 – 11:00						
	00:00	01:00	02:00	**…**	21:00	22:00	23:00
01-Oct-24	158451	44749305	3390268	…	15780697	224674	532306
02-Oct-24	98006	7231713	896560	…	341788	168989	209743
03-Oct-24	17023572	20880926	12247434	…	183615	111703594	177365
04-Oct-24	27308685	820952	5407651	…	1988334	37080	7319359
05-Oct-24	6148531	2053634	71610	…	8753127	26	1793068
…	…	…	…	…	…	…	…
27-Oct-24	14725258	6171503	1478986	…	37992092	9320598	875716
28-Oct-24	2997	25104963	1339389	…	5779011	4155724	879503
29-Oct-24	224744533	543388	131937574	…	109232453	8067753	91304539
30-Oct-24	257101528	12669346	18281277	…	39771157	9630529	945899487
31-Oct-24	235673125	254304426	221250905	…	611630	39513037	133754

d. Mean Absolute Percentage Error (MAPE)

The next stage of the analysis involves calculating the Mean Absolute Percentage Error (MAPE). MAPE measures the percentage of prediction error by comparing the Error values to the actual data, thereby providing a clearer assessment of the Neural Network model's performance. The MAPE calculation results are presented in **Table 12**.

Table 12. MAPE Values

Date & Time	Upload and Download 00:00 – 11:00						
	00:00	**01:00**	**02:00**	…	**21:00**	**22:00**	**23:00**
01-Oct-24	2%	34%	14%	…	11%	1%	5%
02-Oct-24	2%	17%	10%	…	2%	1%	2%
03-Oct-24	18%	23%	24%	…	1%	32%	2%
04-Oct-24	20%	5%	15%	…	5%	1%	13%
05-Oct-24	12%	9%	2%	…	9%	0%	10%
…	…	…	…	…	…	…	…
27-Oct-24	5%	8%	5%	…	15%	10%	3%
28-Oct-24	0%	16%	5%	…	6%	6%	4%
29-Oct-24	42%	3%	76%	…	17%	3%	14%
30-Oct-24	30%	9%	11%	…	11%	6%	86%
31-Oct-24	32%	40%	36%	…	2%	17%	1%

Based on the MAPE values obtained in Table 12, the next step is to calculate the average value for each test conducted. The average MAPE results per test are presented in **Table 13**.

Table 13. MAPE Average Values

Data Label	Date & Time	Average MAPE	Data Label	Date & Time	Average MAPE
DU1	Oct 1 2024	8.32%	DU16	Oct 16 2024	15.93%
DU2	Oct 2 2024	4.39%	DU17	Oct 17 2024	11.10%
DU3	Oct 3 2024	14.73%	DU18	Oct 18 2024	12.13%
DU4	Oct 4 2024	9.17%	DU19	Oct 19 2024	10.60%
DU5	Oct 5 2024	10.34%	DU20	Oct 20 2024	17.00%
DU6	Oct 6 2024	6.60%	DU21	Oct 21 2024	11.65%
DU7	Oct 7 2024	15.22%	DU22	Oct 22 2024	12.51%
DU8	Oct 8 2024	13.29%	DU23	Oct 23 2024	6.16%
DU9	Oct 9 2024	12.32%	DU24	Oct 24 2024	10.51%
DU10	Oct 10 2024	9.28%	DU25	Oct 25 2024	10.84%
DU11	Oct 11 2024	8.20%	DU26	Oct 26 2024	10.55%
DU12	Oct 12 2024	12.89%	DU27	Oct 27 2024	10.67%
DU13	Oct 13 2024	12.43%	DU28	Oct 28 2024	7.89%
DU14	Oct 14 2024	11.29%	DU29	Oct 29 2024	13.47%
DU15	Oct 15 2024	7.65%	DU30	Oct 30 2024	12.44%
			DU31	Oct 31 2024	9.10%

The final stage of the MAPE analysis is the calculation of the average MAPE from the 31 tests, as obtained from Table 13. The calculation process uses Equation 6.

$$Average\ MAPE = \frac{DU1+DU2+DU3+\cdots+DU29+DU30+DU31}{31} \quad (6)$$

$$= \frac{8.32\%+4.39\%+14.73\%+\cdots+13.47\%+12.44\%+9.10\%}{31}$$

$$= \frac{338.66\%}{31}$$

$$= 10.92\%$$

The overall average MAPE of 10.92% indicates that the model's prediction performance can be considered good.

e. Prediction Accuracy

Prediction accuracy is calculated using Equation 7 to quantify how closely the Neural Network's predicted values match the actual observed data. This calculation is essential for assessing the model's reliability and effectiveness in forecasting real-world bandwidth utilization patterns. High accuracy values indicate that the model successfully captures underlying trends, while lower values may suggest the need for further refinement or additional data preprocessing.

$$Model\ Accuracy = 100\% - MAPE \tag{7}$$

$$= 100\% - 10.92\%$$

$$= 89.08\ \%$$

Based on the calculation using Equation 7, the accuracy of the Backpropagation Neural Network model is 89.08%.

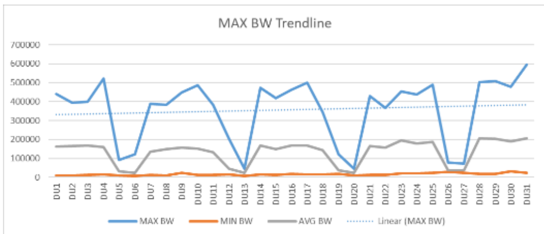


Figure 36. Trend of Maximum Bandwidth Utilization Increase

Using the predicted utilization data over 31 days, the lowest, highest, and average bandwidth usage values were obtained**. Figure 36** visually illustrates that the highest predicted utilization shows an increasing usage trend. This trend in utilization increase can serve as a reference for recommendations in decision-making regarding the bandwidth allocation for future use.

Conclusion

Based on the analysis and evaluation results, the Backpropagation Neural Network model achieved a Mean Absolute Percentage Error (MAPE) of 10.92%, indicating a relatively low prediction error. Consequently, the model's prediction accuracy reached 89.09%. The utilization trend also demonstrates a rising pattern in bandwidth usage over time, which can serve as a reference for future bandwidth allocation planning. These findings suggest that the Backpropagation Neural Network can provide reliable predictions and can be effectively applied to analyze and forecast bandwidth requirements for vertical office networks.

The bandwidth prediction study has limitations regarding the number of attributes used in training the prediction model, as it relies solely on historical bandwidth utilization data. This limitation presents opportunities for further development of the Backpropagation Neural Network model to improve prediction accuracy. Future bandwidth prediction research is expected to benefit companies or institutions that use internet networks as a core operational component by incorporating additional variables, such as the number of applications in use, latency levels, and the number of active users. By including relevant attributes, the model can serve as an enhanced reference for planning or designing more efficient network infrastructure and bandwidth allocation.

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