APPLYING MACHINE LEARNING APPROACHES FOR NETWORK TRAFFIC FORECASTING

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Abstract

In the era of the digital world. The communication and the use the internet is an important role in today's society. As a result, the number of users networks traffic increases but not enough resources for users causing users to receive inefficient services. Therefore, the network service provider must take action to fix the aforementioned problem. Forecasting is therefore necessary in order to determine the amount of network traffic in order to support the future increase in user numbers. Consequently, this research investigates to assess network traffic forecasts comparing the machine learning: Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), and statistical methods: Autoregressive Integrated Moving Average (ARIMA), Simple Moving Average (SMA). The method of sliding window will be used simultaneously and evaluate the forecast and model performance using the MAE, MAPE, MSE, RMSE and R-square algorithms, respectively. The results show that machine learning forecasting is more effective than statistical forecasting. Because the error value is lower, the model can reliably anticipate data. Therefore, the results of this research are expected to help network service provider to improve their networks quickly and efficiently to accommodate the number of users that may increase in the future.

***Keywords*: Machine learning; Forecasting; Artificial Neural Network; Long Short-Term Memory; Autoregressive Integrated Moving Average; Simple Moving Average.**

1. Introduction

Nowadays, the life and well-being of society are being driven by technology. Communication through the online world has resulted in the increasing use of the internet. Therefore, the amount of traffic on the network has increased even more. Using an internet network are described as simple compared to a car and the transmission line is compared to a road. If one day when the number of cars on one of the roads has increased until the car overflows the road causing a bottleneck and causing traffic congestion. It's like having several internet users at the same place and time. As a result, the network system cannot support the use of the service user. This problem causes users to experience inefficient usage such as internet lag, internet speed that is not according to package, etc. Therefore, network operators need to find revise the problem aforementioned necessary have to be predicted the amount of internet usage on the network in the future. In order to allocate resources available on the network provide efficiency as well as sufficient for future service users and will result in more reliable network service providers.

There are various research was studied forecasting network traffic whether its machine learning forecasting or statistical forecasting. In [1] the integration of a model between RKM and SMA to predict online network traffic was examined. It is noticeable that when the models are combined, they can help in planning and designing networks efficiently. A study in [2] predicts uplink traffic in 3G cellular networks with ARIMA, ENN, and MLP. The forecast results showed that ARIMA, ENN, and MLP were able to forecast nonlinear 3G data effectively. A study in [3] proposed a statistical method, namely Decomposition, Winter's Exponential Smoothing, and ARIMA, which predicted Mulawarman University internet usage data for each model. In [4] compare to the uplink and downlink network traffic forecasting capabilities with ARIMA, LSTM, and linear regression models. Both results studies show that the ARIMA model had a lower forecast error rate than the other models. However, in paper [5] predict traffic data in the cellular network, and time series forecasting has been studied [6], in two articles compare the forecasting capability between LSTM and ARIMA models. It can be seen LSTM is more efficient in forecasting accuracy. In article [7], traffic data in TCP/IP network from two providers, split by minute, hour, and day, where compared forecasting, are compared with MLP-BP, MLP-RP, RNN, and SAE. It may be considered that the RNN has better forecasting performance because it has a smaller NRMSE value and can predict the data more quickly. Article [8] contrasts the forecasting performance of telecommunication network usage data with LSTM, GRU, ANFIS, ANN, and GMDH models. The illustrate that the LSTM and GRU were more predictable than other models due to the smaller RMSE, MAPE, MAE values, the R is close to 1, and Theil's U-statistic is close to 0. In [9] proposes a forecast of mobile networks by comparing between ANN and linear prediction, ANN considers the length of the observation window. The results showed that the ANN was more predictable and required a shorter observation window length. And [10] proposes the use of a prediction ANN model to detect abnormalities in network traffic that indicates whether the network has been compromised or not. The ANN uses a series of weight updates is Gradient Descent, and Momentum and the results indicate that the ANN can predict network traffic anomalies. This research requires real-time network traffic usage forecasting to be able to support the number of users per minute from studying various research It was found that most of the research has not to forecast the data in real-time. Therefore, this research presents a sliding window method to assist in real-time data forecasting it will be used in conjunction with machine learning methods such as ANN, LSTM, and statistical methods such as SMA, ARIMA, then will evaluate the performance of each model used in forecasting.

2. Background Theory

2.1. *Simple Moving Average (SMA)*

The SMA, also known as single moving average, is a part of moving average (MA) suitable for forecasting abnormal and a little volatile time-series data. The working principle of SMA is to combine the values of a number of historical data and after that take to find the mean and forecast future data [11]. Which in the process of working will give equal weight to all historical data [12]. The first stage in calculating the SMA is to calculate the moving average, followed by forecasting as stated in the equation below.

$$MA(k)_t = \frac{1}{k}\sum_{i=t-k+1}^{t} y_i \ . \tag{1}$$

$$\hat{Y}_{t+1} = MA(k)_t \ . \tag{2}$$

where, k : the amount of historical data is a positive integer, y_i : past data value, $MA(k)_t$: moving average at time t , and $\hat{Y}_{t+1}$: prediction value at time t .

2.2. *Autoregressive Integrated Moving Average (ARIMA)*

ARIMA is a powerful statistical forecasting tool it analyzes the available data as a time series. It will use historical data to predict future data and give importance to every data both historical data as well as forecasting from moving average. ARIMA is a combination of three components, known as an "order" is Autoregressive (AR), Integrated (I), and Moving Average (MA), also known as ARIMA(p,d,q), where p is the number of coefficients of AR, q is the number of coefficients of MA [13] and d is the number of times the difference is determined. To eliminate seasonality components of variance and make time-series data stationary [14]. The AR(p) model selection was based on the partial autocorrelation function (PACF), and the MA(q) model selection was based on the auto correlation function (ACF), shown in equations 3 and 4 respectively [2].
Autocorrelation:

$$P_k = \frac{\sum_{t=k+1}^{T} (y_t - \bar{y})(y_{t-k} - \bar{y}_{t-k}) / (t-k)}{\sum_{t=1}^{T} (y_t - \bar{y})^2 / T}. \tag{3}$$

where,

$$\bar{y}_{t-k} = \sum y_{t-k} / (T-k).$$

Partial Autocorrelation:

$$= \frac{Covariance(X_t, X_{t-2} \mid X_{t-1})}{\sqrt{Variance(X_t \mid X_{t-1}) Variance(X_{t-2} \mid X_{t-1})}}. \tag{4}$$

To make is time-series data stationary the number of differences d is performed as shown in equation 5 [15].

$$\Delta^d X_t = \Delta^{d-1} X_t - \Delta^{d-1} X_{t-1}. \tag{5}$$

Where, d : the order of differences and Δ^d : the command differential operator d .

2.3. *Artificial Neural Network (ANN)*

ANN or Neural Network is a model for forecasting with machine learning which can analyze and forecast time-series data. The ANN functions similarly to the human brain. This property of ANN can learn the information that feeds into the network and calculate with a computer system from a mathematical model. There are three layers in the ANN model: the input layer, hidden layer, and output layer, each with a distinct number of neurons. The first layer, the function of the input layer is to feed inputs into the model, and the number of neural relies on the inputs or feature that want the model to learn. The second layer, the hidden layer, is in charge of processing and takes the input that combines the preceding layer's weights and sums them with the bias. Then the sum will be calculated using a linear, relu, or sigmoid activation function. This layer can have any number of layers of neurons but increasing or lowering the number can affect the model's performance. The final layer, the output layer, will display the results of the previous layers calculations. If it is a regression model forecast, there is only one neuron in this layer. The building of the ANN model is depicted in Figure 1, while the model is functioning is depicted in equations 6 and 7.

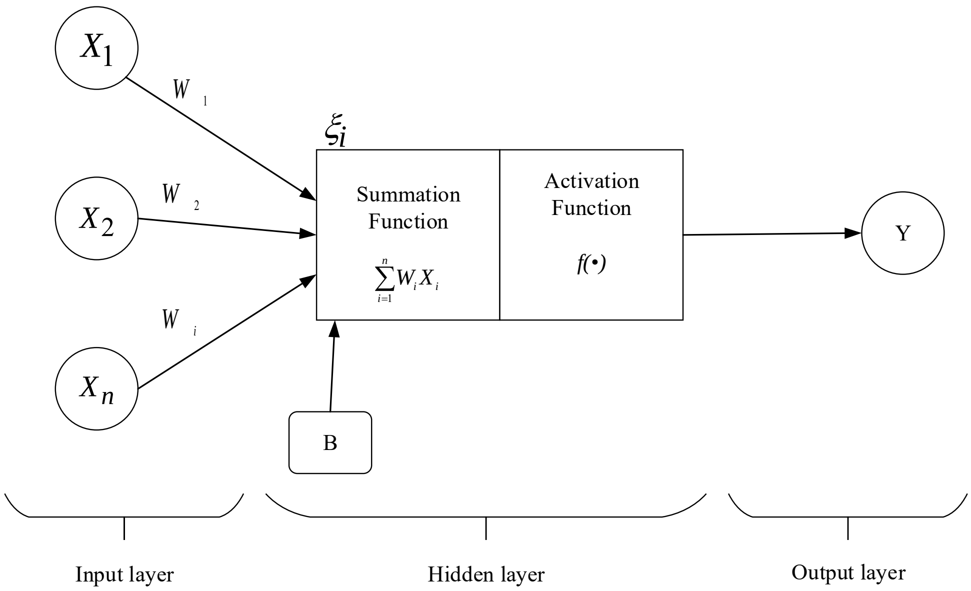

Fig. 1. Structure and concept of operation of the ANN model [16].

can be equation written as [16]:

$$\xi_i = \sum_{i=1}^{n} W_i X_i + B. \tag{6}$$

$$Y = f(\sum_{i=1}^{n} W_i X_i + B). \tag{7}$$

Where; ξ_i : sum function between input, weight, and bias, X_i : input data of neuron i , W_i : the weight of each link between the neurons, B : bias value, $f(\bullet)$: activation function, and Y : output node of neuron.

2.4. *Long Short-Term Memory (LSTM)*

The LSTM is a neural network in Recurrent Neural Network (RNN) family that was developed to correct gradient vanishing of RNN and increase memory cell stage. The LSTM can process or forecast sequential time-series data. The LSTM network consists of four cell gates: an input gate, an input modulation gate, a forget gate, and an output gate. The LSTM function at that forget gate will control the cell stage in memory if 1 preserves the cell stage in memory, but 0 deletes it. The input gate and input modulation gate control the new input data and check whether or not it can be used to update the cell stage. If an update is possible, the input modulation gate will perform the update with function tanh. The output gate decides which data to send out of the memory to get the result. The following equation can be used to define the LSTM is working principle [17][18] and Figure 2 depicts the internal structure of the LSTM:

$$f_t = \sigma(W_f \cdot [h_{t-1}, X_t] + b_f), \tag{8}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, X_t] + b_i), \tag{9}$$

$$c_t' = \tanh(W_c \cdot [h_{t-1}, X_t] + b_c), \tag{10}$$

$$c_t = f_t * c_{t-1} + i_t * c_t', \tag{11}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o), \tag{12}$$

$$h_t = o_t * \tanh(c_t). \tag{13}$$

Where; x_t : input vector, w : weight, σ : sigmoid function, h : hidden stage, b : bias vector, c_t : cell stage, f_t : forget gate, i_t : input gate, c_t' : input modulation gate, and o_t : output gate.

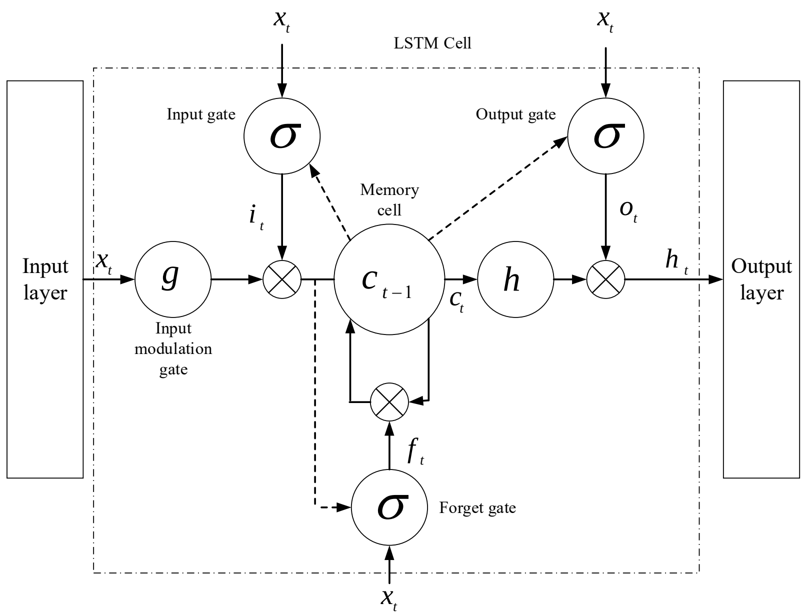

Fig. 2. The LSTM model structure and operation [8].

2.5. *Performance tool*

The tools used to measure the performance of network traffic forecasting for each model are as follows:

2.5.1. Mean Absolute Error (MAE)

It is a measure of the difference between the forecasted and actual data to evaluate if the discrepancy is greater or lesser. A model is considered efficient if its MAE value is low.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - x_i\right| . \tag{14}$$

Where; y_i : data forecasting, x_i : actual data, and n : number of samples total.

2.5.2. Mean Absolute Percentage Error (MAPE)

It is a measure of a model's correctness or mistake in the form of an absolute percentage. The better the performance, the lower the MAPE value.

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - x_i}{x_i}\right| . \tag{15}$$

2.5.3. Mean Squared Error (MSE)

It is a metric for calculating the squared average error between forecast and actual data. The model is more accurate if the MSE value is low.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - x_i\right)^2 . \tag{16}$$

2.5.4. Root Mean Squared Error (RMSE)

It is a metric for measure average size of the error between forecasted and actual data. The lesser the RMSE, the better.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} . \tag{17}$$

2.5.5. R-squared (R^2)

It is a metric for how well a model can predict, by measure between the forecast data and the actual data. The model is performing well if R approaches 1 or 100 percent.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \overline{y})^2} . \tag{18}$$

where, $\overline{y} = \frac{1}{n}\sum_{i=1}^{n} x_i$: mean of actual data.

3. Methodology

3.1. *Input Dataset*

The network traffic data set, which comprises of two sets of data, will be analyzed, and forecast in the future in this research. The first data set from research [19] can access and download from http://www3.dsi.uminho.pt/pcortez/data/itraffic.html. Data collected from private ISP located at centers in 11 European cities from June 7, 2005, at 6:57 AM. to July 28, 2005, at 11:17 AM. was collected every 5 minutes (in bits per sec) to forecast.

The second set of data comes courtesy of the Computer Center of the Suranaree University of Technology. By collecting traffic data on the university network system was collected every 5 minutes (bit per sec) from June 15, 2021, at 00.00 AM. to July 15, 2021, at 03:35 AM. The data consists of date, time, the number of users, average incoming, and average outgoing, and in this research, it will forecast average incoming and average outgoing.

3.2. *Experiment*

ANN, LSTM, and ARIMA are machine learning forecasting tools and statistical methodologies, respectively it is presented by python computer programming on Google Cloud Platform namely Google Colab. Machine learning forecasting uses the Keras tool, a library in running high-performance models. The statistical forecasting section of SMA performs forecasting using excel. After forecasting future traffic, it will perform forecast evaluation and model performance with the MAE, MAPE, MSE, RMSE, and R-square algorithms, respectively.

3.2.1. Machine learning methods

Data is forecasted by two algorithms, ANN and LSTM, and the dataset is partitioned into two to forecast network traffic using machine learning methods. Figure 3 depicts the forecasting method.

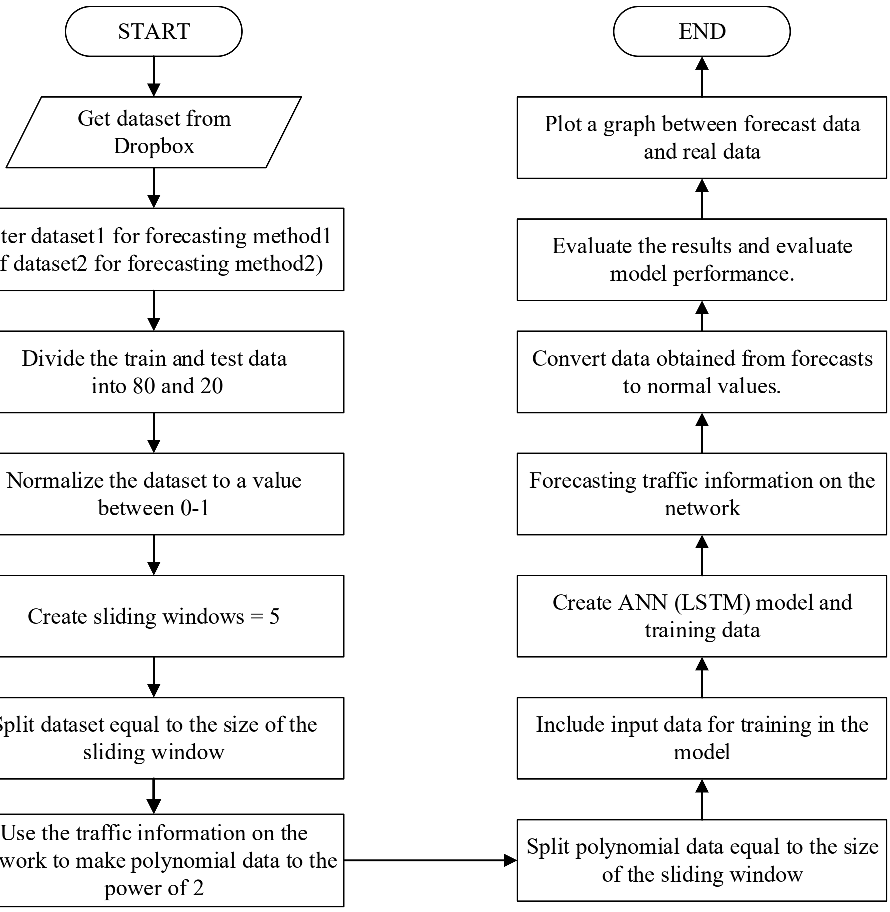

Fig. 3. Shows the forecasting methods of the ANN and LSTM algorithms.

Dataset 1 is a collection of network traffic volumes of 11 European cities. Network traffic data and polynomial network traffic data raised to the power of two are utilized for forecasting. For the forecasting process. It retrieves a cloud-stored dataset called Dropbox and performs filter traffic on the network system. The traffic data was split into two parts, with 80 percent being training datasets and 20 percent being testing datasets. Then, using MinMaxScaler, convert the data values to the same range and normalizing the data to be between 0-1. Then, we will create a sliding window with a value of 5, i.e., take 5 values from the past to forecast the future value, which is 6. (e.g., network traffic volume in the past 25 minutes to predict the future value at the 30 minutes). Once the sliding window has been created, the normalized network systems traffic volume data is divided equally by the sliding windows size, yielding the data for input#1. Then take the normalized traffic volume data to make a polynomial to the power of 2 and divide the data equal to the size of the sliding window, yielding input#2 and then sum input#1 to input#2 which will get input total. Afterward, proceed to model the ANN and LSTM algorithms the parameters for training are shown in Table 1. Following that, the model will be trained using 80 percent of the total input, and the test will use the remaining 20 percent of the data to estimate future data values. And the data obtained from the forecast is converted back from values in the range of 0-1 back to normal values. The experimental data and model performance were then evaluated using the MAE, MAPE, MSE, RMSE, and R-square approaches, respectively. Finally, the results obtained from the forecast are compared with the actual network traffic by plotting graphs.

The second data set is the traffic volume on the Suranaree University of Technology network system unlike data set 1 by dataset divides network traffic volume into average incoming and outgoing traffic, as well as the number of users. In forecasting is divided into two cases. Average incoming and average outgoing are the first and second cases, respectively. In case 1, the inputs for the model to train and the forecast will have three inputs: input#1: network traffic volume of average incoming, input#2: Polynomial to the power of 2 of average incoming, and input#3: the number of users.

In case 2, the model learns from the following input data: input#1: network traffic volume of average outgoing, input#2: Polynomial squared of average outgoing, and input#3: the number of users. Then arrange the input data to equal the size of the sliding window. Once the data is formatted, the inputs are concatenated first and trained on the data within the model. It will then forecast the data and evaluate the model's performance. The forecasting method is the same as in dataset 1 or in Figure 3 experimental procedure diagram.

Parameter	Data from 11 city in Europe		Data from network inside university Average Incoming / Average Outgoing	
	ANN	LSTM	ANN	LSTM
Polynomial of network traffic	The power of 2		The power of 2	
Number of hidden layers	2		2	
Number of neurons in hidden layer	128		128	
Activation function in hidden layer	relu		relu	
Number of output layers	1		1	
Number of neurons in output layer	1		1	
Activation function in output layer	linear		linear	
Clients Count	No		Yes	
Epochs	200	100	200	100

Table 1. Parameter designated for training of ANN and LSTM

3.2.2. *ARIMA Model*

For network traffic volume forecasting using statistical methods is the ARIMA model, the forecast is divided into two data sets, and the forecasting process is shown in Figure 4.

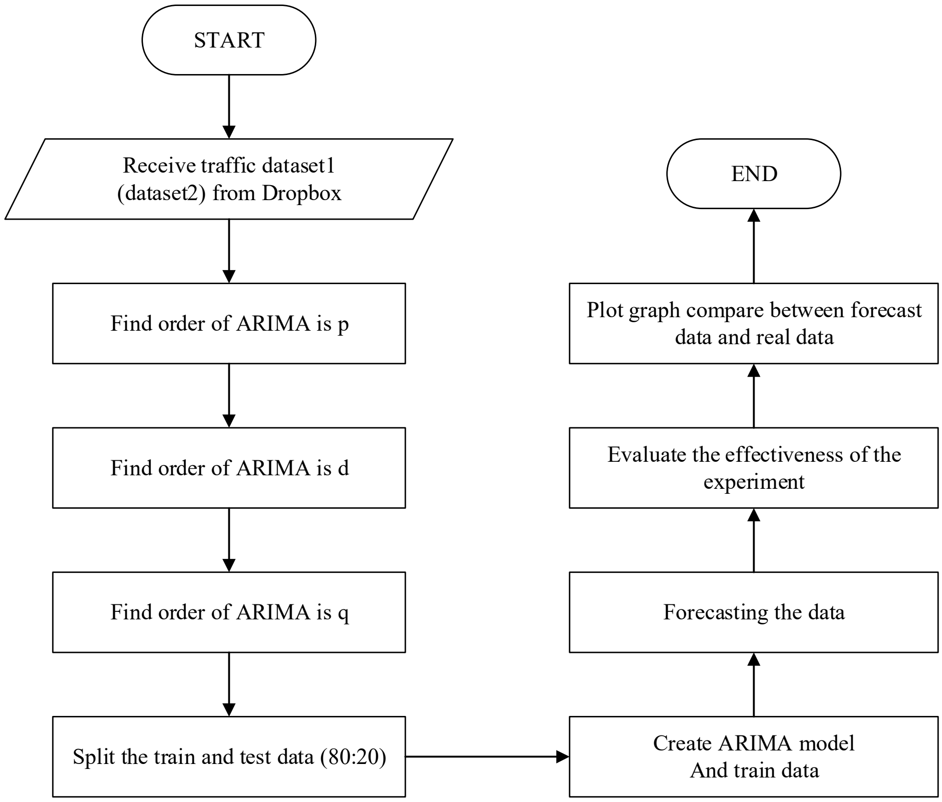

Fig. 4. The forecasting process using ARIMA statistical methods.

Data preparation principles, data training, data forecasting, forecasting performance measurement, and model performance evaluation will use the same method as ANN and LSTM. To use ARIMA to anticipate data, the first step is to extract network traffic volume from Dropbox, a cloud service. The first data set is network traffic volume data from 11 cities in Europe, and the second data set is network traffic volume within the university, divided into average incoming and average outgoing traffic, then carry out find order (p,d,q) used to create a forecasting model.

To find an order, it first it checks the raw data whether the raw data is stationary or not. Which will the Dickey-Fuller Test was used to determine whether the data was stationary, which P-values less than 0.05 indicate that the data is stationary, hence the resulting d-values do not need to make a difference. Then plot the PACF graph to find the AR value or p-value, which will measure the relative value of the data and the method used is "ols.". The p-value is then calculated from the graph using a confidence interval of 95 percent and the graph intersection, which will be at 1.96. And the last order is the MA value or q, which will the measured relationship of the data by plotting the ACF graph. The graph intersection with the 95 percent confidence interval is then used to determine the q-value. And table 2 shows order at used creating an ARIMA model to data forecasting.

The model will then be constructed using the previously discovered order. and divide the training data by 80 percent and testing data by 20 percent. It feed training data into the model so that it can learn and forecast the rest of the test data. After that, once the data set has been forecasted, will experimental evaluation and forecast performance is with MAE, MSE, RMSE, and R-square, respectively, and will plot graphs showing the comparison of the actual data with the forecasting data.

Parameter	**Data from 11 city in Europe**	**Data from network inside university**	
		Average Incoming	**Average Outgoing**
Order for model (p, d, q)	(2,0,0)	(3,0,1)	(3,0,0)

Table 2. Parameter designated for training in ARIMA

3.2.3. SMA Model

For forecasting data using statistical methods using the SMA model, it is calculated which use excel. The forecasted data is the network traffic of 11 European cities and the network traffic within the university network are average incoming and average outgoing. Where taking five past values, $k = 5$ and calculating find the $MA(k)_t$ according to equation (1), for example, bring five past values, or values from the last 25 minutes, add them together and divide by k. Then, after calculating the movement value, it predicts the next future value, such as the value at time 6 or the value at 30 minutes and calculates find the value of $\hat{Y}_{t+1}$ using equation (2). When the data forecast is finished, the forecast performance is check, and the model and plot's efficiency is compared, afterward graph will be showed to compare the actual data and the forecast data.

4. Result

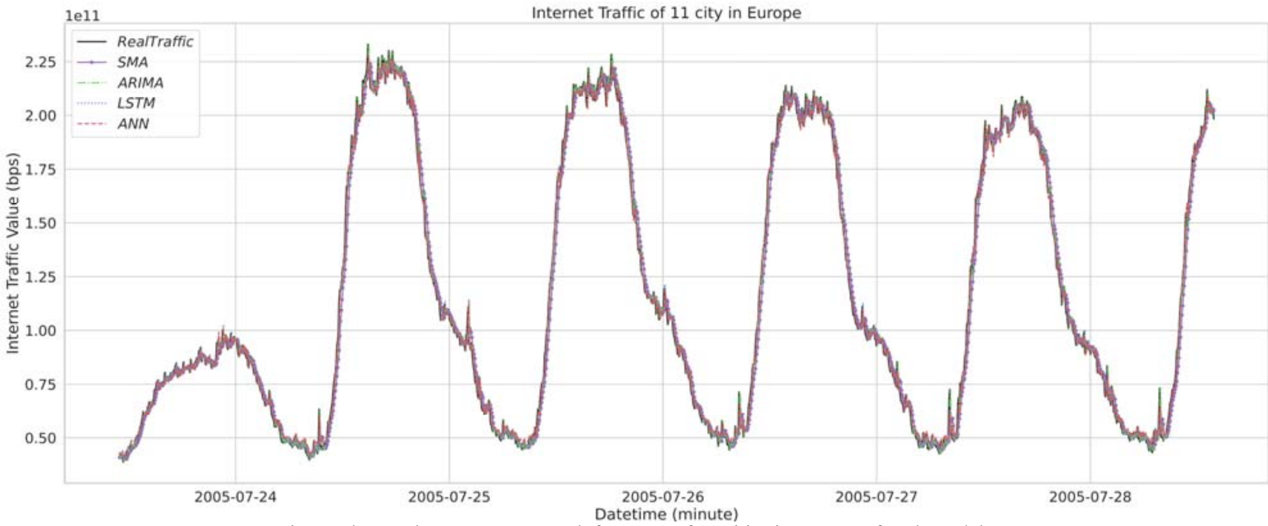

Fig. 5. The graph compares network forecasts of 11 cities in Europe of each model.

Model	MAE	MAPE	MSE	RMSE	R^2
SMA	4.59×10^9	4.45	4.18×10^{19}	6.47×10^9	0.990
ARIMA	2.89×10^9	76.12	1.62×10^{19}	4.03×10^9	0.9957
LSTM	2.93×10^9	3.15	1.54×10^{19}	3.93×10^9	0.9959
ANN	2.94×10^9	3.19	1.53×10^{19}	3.91×10^9	0.9960

Table 3. The performance of each model forecasting data for 11 cities in Europe.

After forecasting the amount of traffic on the network successfully, the results can be displayed as follows. The result of the first set of data, network traffic volumes of 11 European cities, is shown in Figure 5, it can be seen the comparison of the forecasts of each model and comparing it with the actual data. Within the graph contains, the vertical axis represents the network traffic volume (in bps), and the horizontal axis represents the date and time (unit in seconds). The predictive data using machine learning is ANN and LSTM, as demonstrated in red and blue lines, it is more effective in forecasting than statistical forecasting, as shown in the graph, because the graph is nearby to the actual data line (black line). And the predictive performance of each model was tested with MAE, MAPE, MSE, RMSE and R-square as shown in Table 3. The ANN model has forecast efficiency 2.94×10^9, 3.19, 1.53×10^{19}, 3.91×10^9, and 0.9960 respectively. And the LSTM model is effective in forecasting is 2.93×10^9, 3.15, 1.54×10^{19}, 3.93×10^9, and 0.9959 respectively. It can be seen the ANN and LSTM models offer lower prediction errors than the ARIMA and SMA models.

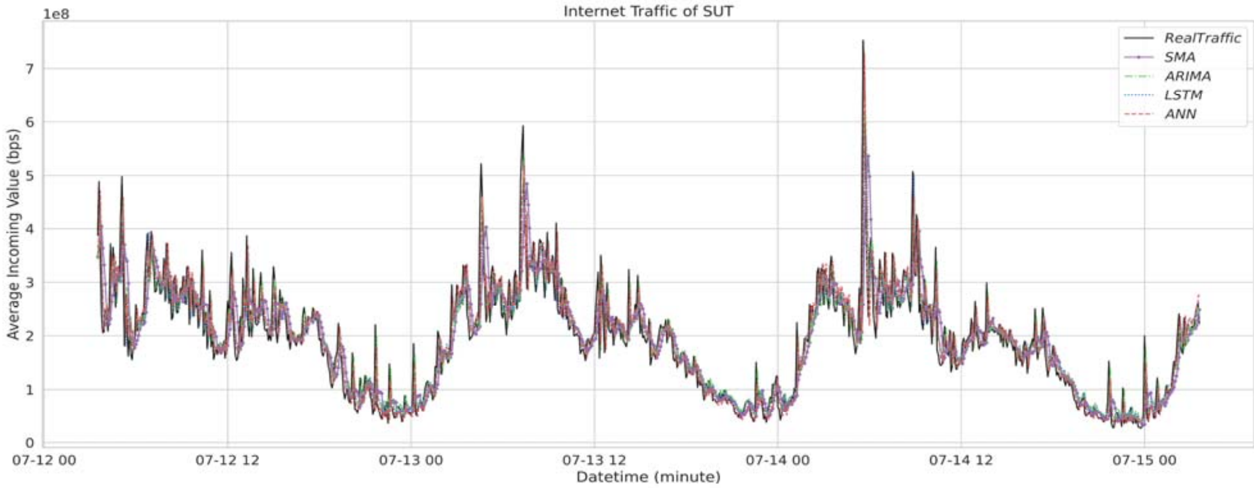

Fig. 6. The graph compares network forecast average incoming of SUT for each model.

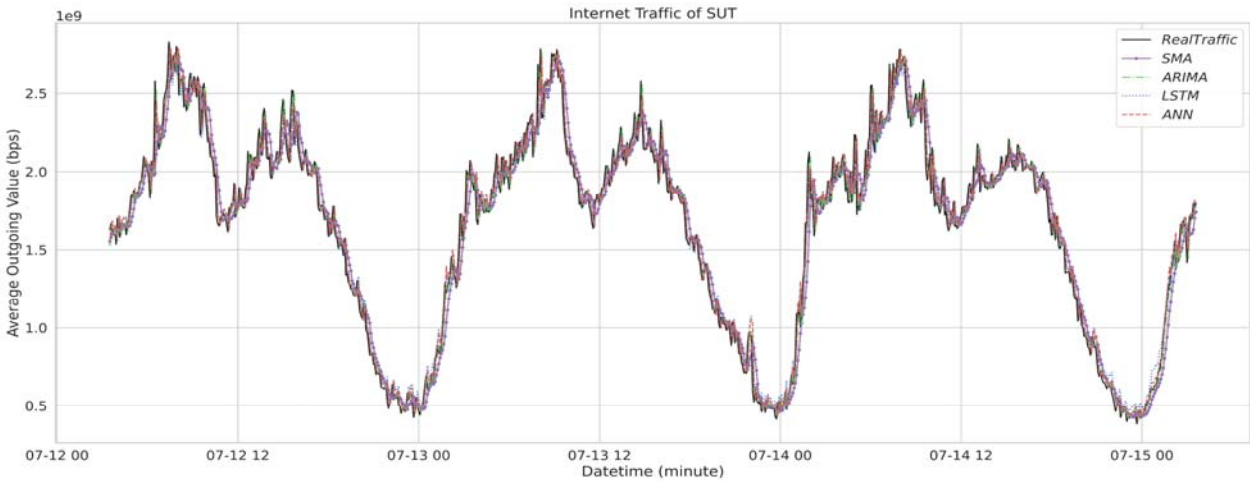

Fig. 7. The graph compares network forecast average outgoing of SUT for each model.

Model	Average Incoming					Average Outgoing				
	MAE	MAPE	MSE	RMSE	R^2	MAE	MAPE	MSE	RMSE	R^2
SMA	4.83×10^6	16.53	5.49×10^{13}	7.41×10^6	0.7838	1.46×10^7	6.43	3.72×10^{14}	1.93×10^7	0.9723
ARIMA	3.67×10^6	79.52	3.29×10^{13}	5.74×10^6	0.7980	9.11×10^6	68.32	1.56×10^{14}	1.25×10^7	0.9795
LSTM	3.63×10^6	15.37	3.45×10^{13}	5.87×10^6	0.7878	9.83×10^6	5.35	1.78×10^{14}	1.33×10^7	0.9767
ANN	3.59×10^6	15.11	3.06×10^{13}	5.53×10^6	0.8117	9.03×10^6	4.76	1.53×10^{14}	1.24×10^7	0.98

Table. 4. The performance of each model forecasting data for SUT network.

The result from the second set of data is the traffic volume on the network system inside the university. Figure 6 indicate a graph comparing the results of the average incoming of each model against the actual data. It is noticeable that the ANN and LSTM model (red and blue lines, respectively) had more predictive results that were closer to the actual data (black lines) than ARIMA and SMA. When the model efficiency was evaluated using the parameters listed in Table 4, it was discovered that both models had lower error levels. Where the model efficiency ANN is 3.59×10^6, 15.11, 3.06×10^{13}, 5.53×10^6,and 0.8117 respectively. The efficiency of the LSTM model is 3.63×10^6, 15.37, 3.45×10^{13}, 5.87×10^6, and 0.7878 respectively.

In term of the results from the average outgoing test, it is illustrated in Fig. 7, will comparing the forecast results of each model with the actual data, it is found that the ANN and LSTM models (red and blue lines, respectively) yield results forecast close to actual data (black line). When comparing the efficiency of each model, the ANN and LSTM have lower predicted error values than the ARIMA and SMA, as shown in Table 4. The efficiency of a ANN model is 9.03×10^6, 4.76, 1.53×10^{14}, 1.24×10^7, 0.98 respectively. And the efficiency of a LSTM model is 9.83×10^6, 5.35, 1.78×10^{14}, 1.33×10^7, 0.9767 respectively.

From the forecasting of both datasets, the ANN and LSTM models had an R-square approach closer to 1 as shown in Table 4, meaning the model had more accurate forecasting performance than ARIMA and SMA. As a result, forecasting using machine learning is proven to be more effective than predicting using statistical methods. For the forecast time of each model, ANN forecast time is about 5 minutes, LSTM forecast time is 30-40 minutes, and ARIMA forecast time is 20 minutes-1hour depends on the amount of data to be forecast that there is a lot or little. As a result, ANN outperforms LSTM in terms of forecasting time but if using LSTM for forecasting, it may not be able to respond to real-time forecasting. Because, when used to a real network system, speed of forecasting is required in order to allocate the network in a timely manner to satisfy the needs of users.

5. Conclusion

Forecasting network traffic volume from both datasets is nonlinear, with machine learning methods and statistical methods and will also incorporate sliding window methods. To forecast data in real time, such as data for the next 30 minutes based on the previous 25 minutes data. Based on the metrics MAE, MAPE, MSE, RMSE, and R-square, it was discovered that forecasting with machine learning methods, ANN, and LSTM model, has superior performance and accuracy, and is also less error-prone than statistical approaches ARIMA and SMA. However, using the machine learning approach used in this study, the ANN model has an advantage over the LSTM model in that it spends less time forecasting. Therefore, the ANN model is more suitable. Because in this research, the need to forecast the data quickly and efficiently. In order to support the use of users in rea- time, the internet network service providers can also upgrade and allocate the network system to be sufficient for the number of users that will increase in the future.

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References

[1] Aldhyani, T. H. and Joshi, M. R. (2017): Enhancement of Single Moving Average Time Series Model Using Rough k-Means for Prediction of Network Traffic, International Journal of Engineering Research and Application, vol. 7, pp.45-51.
[2] Oduro-Gyimah, F. K. and Boateng, K. O. (2018): A comparative analysis of telecommunication network traffic forecasting: A three model approach, 2018 IEEE 7th International Conference on Adaptive Science & Technology (ICAST), pp. 1-11.
[3] Purnawansyah, P.; Haviluddin, H.; Alfred, R. and Gaffar, A. F. O. (2018): Network traffic time series performance analysis using statistical methods, Knowledge Engineering and Data Science (KEDS), vol. 1, no. 1, pp. 1-7.
[4] Lv, T.; Wu, Y. and Zhang, L. (2021): A Traffic Interval Prediction Method Based on ARIMA, in Journal of Physics: Conference Series, vol. 1880, no. 1, pp. 012031.
[5] Azari, A.; Papapetrou, P.; Denic, S. and Peters, G. (2019): Cellular traffic prediction and classification: A comparative evaluation of LSTM and ARIMA, International Conference on Discovery Science, pp. 129-144.
[6] Zhou, K.; Wang, W. Y.; Hu, T. and Wu, C. H. (2020): Comparison of Time Series Forecasting Based on Statistical ARIMA Model and LSTM with Attention Mechanism, Journal of Physics: Conference Series, vol. 1631, no. 1, pp. 012141.
[7] Oliveira, T. P.; Barbar, J. S. and Soares, A. S. (2016): Computer network traffic prediction: a comparison between traditional and deep learning neural networks, International Journal of Big Data Intelligence, vol.3, no. 1, pp. 28-37.
[8] Do, Q. H.; Doan, T. T. H.; Nguyen, T. V. A.; Duong, N. T. and Linh, V. V. (2020): Prediction of Data Traffic in Telecom Networks based on Deep Neural Networks, Journal of Computer Science, vol. 16, no. 9, pp. 1268–1277.
[9] Kirmaz, A.; Michalopoulos, D. S.; Balan, I. and Gerstacker, W. (2020): Mobile Network Traffic Forecasting Using Artificial Neural Networks, 2020 28th International Symposium on Modeling, Analysis, and Simulation of Computer and Telecommunication Systems (MASCOTS), pp. 1-7.
[10] Ciptaningtyas, H. T.; Fatichah, C. and Sabila, A. (2017): Network traffic anomaly prediction using Artificial Neural Network, AIP Conference Proceedings, vol. 1818, no. 1, pp. 020010.
[11] Chiulli, R.M. (1999). Quantitative Analysis: An Introduction, Gordon and Breach Science Publishers, pp.234.
[12] Yaffee, R. and McGee, M. (2000). An Introduction to Time Series Analysis and Forecasting, Cambridge: Academic Press, pp. 18.
[13] Carlberg, C. (2013). Predictive Analytics: Microsoft Excel, Indianapolis: QUE, pp. 243.
[14] Fan, J. and Yao, Q. (2005). Nonlinear Time Series: Nonparametric and Parametric Methods, New York: Springer, pp. 14.
[15] Lu, S.; Zhang, Q.; Chen, G. and Seng, D. (2021): A combined method for short-term traffic flow prediction based on recurrent neural network, Alexandria Engineering Journal, vol. 60, no. 1, pp. 87-94.
[16] Alaloul, W. S. and Qureshi, A. H. (2020): Data processing using artificial neural network, Dynamic Data Assimilation-Beating the Uncertainties.
[17] Wang, S.; Zhuo, Q.; Yan, H.; Li, Q. and Qi, Y. (2019): A network traffic prediction method based on LSTM, ZTE Communications, vol. 17, no. 2, pp. 19-25.
[18] Andreoletti, D.; Troia, S.; Musumeci, F.; Giordano, S.; Maier, G. and Tornatore, M. (2019): Network traffic prediction based on diffusion convolutional recurrent neural networks, IEEE INFOCOM 2019-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), pp. 246-251.
[19] Cortez, P.; Rio, M.; Rocha, M. and Sousa, P. (2012): Multi-scale Internet traffic forecasting using neural networks and time series methods, Expert Systems, vol. 29, no. 2, pp. 143-155.

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