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Bandwidth Provisioning for 4G Mobile Network Using Hybrid ARIMA-LSTM Based Traffic Forecasting

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Abstract : *Several prediction methods currently help companies improve efficiency, one of which is the prediction of bandwidth allocation. This method is expected to support a telecommunications company in carrying out cost efficiency, especially the data transfer cost from each location. Currently, the problem with telecommunication companies is the lack of management of the amount of bandwidth required. Sometimes, there is a lack or excess of bandwidth allocation in each BTS, so that this problem can reduce the profits earned by the company. From these problems, we need a system that can regulate and predict future bandwidth requirements. So in this study, we explore the prediction of bandwidth needs by utilizing the data from monitoring the bandwidth of each cell in the form of time-series data. Researchers collect the data from November 2019 to January 2020; our first step is to simulate predictions using the ARIMA method. In this study, simulations using a combined method of ARIMA and LSTM RNN. After trying several ARIMA and LSTM models, the best models are ARIMA (0.0 .6) and LSTM (windows = 100, 2 Layer, 100 Neuron), where the RMSE results obtained are 387.693019. From the results of the model, the researcher conducted an experiment using the Hybrid ARIMA LTSM model. The findings of this study indicate that predictions within 50 hours indicate an accurate level of accuracy.*

Keywords: *Arima, Timeseries, Bandwith, Payload.*

I. INTRODUCTION

In the field of technology, especially communication, the role of telecommunications companies is crucial in maintaining the quality of the network they have, so that a practical network planning foundation is needed [1], [2] at this time, the calculation of the provision of bandwidth resources is based on the amount of traffic measured at peak times.

Inefficient in terms of resource utilization [3], thus encouraging other technologies in calculating bandwidth resource requirements. The process of calculating bandwidth requirements can be done by searching for patterns in groups or called data mining [4]. So that in the future, the use of this technology in telecommunications companies will be a significant step in making pre-deployment forecasts of the high demand for mobile broadband services [5]. This is supported by the substantial amount of data owned by providers, but this amount of data has not been utilized properly. We see company-owned data vary widely with timeframes from a few seconds to minutes, which can be used for monitoring or as a warning when there is an on-site disturbance. Data with an hourly timeframe can be useful for engineering network traffic where telecom operators can change the flow. Network from busy channels to unused channels, which is the basis of our study, utilizes hourly data to make predictions.

Some of the literature that we studied used two methods, namely statistical methods and machine learning. When the traffic system is less complex, and small-scale data dimensions are used, statistical methods are used with the auto-regressive integrated moving average (ARIMA) model [6] - [8] and when the data contains seasonal factors or has a tendency to repeat the pattern of movement behavior in a period of seasons. Use of the seasonal auto-regressive integrated moving average (SARIMA) model [9]. When the traffic system is very complex and the data dimensions are very large, machine learning methods are used such as support vector machine (SVM) [10] [11] [12] [13], extreme learning machine (ELM) [14], k-nearest neighbor (k -NN) [15] [16] [17], Random Forest [18] [19], and artificial neural networks (ANN) [20] [21]. However, statistical methods have drawbacks when faced with complex problems. So that the use of the Machine Learning method can overcome the weaknesses of statistical methods in the dimensions of large-scale data and non-linear data. However, machine learning methods have limitations when it comes to spatial and temporal relationships of traffic patterns [22] [23] [24]. These two methods have begun to be developed along with technological developments to solve traffic forecasting problems, especially for spatial relationships and temporal traffic forecasting. Machine learning methods such as Deep Neural Networks (DNNs) with representational accuracy resulting in high accuracy metrics and low error rates in handling traffic components [25] [26] [27], Recurrent Neural Networks (RNNs) with short-term traffic prediction and especially long-term approach to Long short-term memory (LSTM) and Gated Recurrent Unit (GRU) [28] [29], Convolutional Neural Networks (CNNs) with the capacity to model the spatial relationship of traffic [30]. Even though the development of the three machine learning methods looks superior, it still has shortcomings

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such as DNN, which still chooses data, especially in the specificity of the path data, RNN, which is less complex in capturing several noises and spurious relationships, and CNN which cannot represent three-dimensional images, especially in spatial relationships. The Euclidean room. Statistical methods such as ARIMA and SARIMA tend to be left behind compared to the development of machine learning methods because the potential of a statistical approach for traffic forecasting cases is not fully exploited. Whereas in some cases outside the case of traffic forecasting, such as hybrid ARIMA in the case of forecasting water resources in Gaza Palestine [31], ARIMA is combined with LSTM in the case of forecasting foodstuffs [32], and LSTM and ANN are combined with ARIMA with Moving Average (MA) in the case of forecasting the cement industry [33] resulted in a satisfactory performance. This study proposes forecasting traffic data time series using the ARIMA method combined with LSTM based on previous research [31], which uses the ARIMA-NN hybrid method.

In contrast, in this study, we chose to use the ARIMA-LSTM hybrid method; the choice of both methods was due to its accuracy. ARIMA method on linear data while LSTM on non-linear data. The model (ARIMA) makes adjustments and estimates the noise data to get the residue and prediction results. The value of the residue is used to train the LSTM model. Furthermore, the ARIMA prediction error is used as an LSTM to improve the ARIMA prediction results [34].

II. PREDICTION MODELS

A. *Time Series*

Time Series is a sequence of events where the next event is determined by one or more previous events, reflecting the process that is being measured. There is one particular component that affects the behavior of a process. Time Series includes methods for analyzing time-series data to extract useful patterns, trends, rules, and statistics. It is built based on the sequence of data points and the distance of the data points with different levels of time-series form, meaning that each data point has its own importance to the time series. This is also considered as the significance of the data points [35]. Meanwhile, Time Series forecasting is a series of sequential events or observations measured continuously at the same time interval.

B. *ARIMA (Auto-Regressive Integrated Moving Average) Model*

a) The AR (Auto-Regressive) Model

In the Auto-Regressive Model, it can be seen from each observation in a time bracket that is connected consistently and one or more previous statements from the same series can be identified; this model can function defined as:

$$Z_t' = \phi_1 Z'_{t-1} + \phi_2 Z'_{t-2} + \ldots + \phi_p Z'_{t-p} + a \qquad (1)$$

Where the AR model is denoted by p with a parameter that indicates the AR model is ϕ. in the AR process, the Autocorrelation function (ACF) will decrease following the exponential or sine waveform while the Partial autocorrelation function (PACF) in the MA process will be disconnected after the lag p can be seen with its structure ϕkk = 0 where k > p

b) MA Model

The MA model is the average form of the seasonal or cyclical component in an adjusted period which serves to smooth the original time series with an intermediate rolling subset of the original series elements [36], the MA model of order q, where the parameters indicate the MA model is ϕ. can be defined as

$$Z_t = a_t - \phi_1 a_{t-1} - \phi_2 a_{t-2} - \ldots - \phi_q a_{t-q} \qquad (2)$$

The ACF structure in the MA model is pk = 0 where k> q or disconnects after laq q, whereas in PACF, it is dominated by a linear combination of the damped sine wave exponential form.

c) The ARMA (Auto Regressive Moving Average) Model

In the ARMA model, which is a mixture of AR and MA models where AR is the p-value and MA is the q value so in general, the form of equations of the mixed model AR and MA are:

$$\phi_p(B)^d \; Z_t = \theta_q(B) \; a_1 \qquad (3)$$

Where in the ARMA process (p, q), ACF is down after the lag to (q-p), and PACF will also decrease in lag (q-p)

d) ARIMA Model

In the ARIMA process, there are two approaches in modeling where if the series of objects is different and the time to achieve stationarity can be modeled with ARIMA (p, d, q) where I show integrated, it can be concluded that the ARIMA model is the most common model in predicting a time series that can be stationary with transformations. Such as differencing and logging [36], so it can be defined as:

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B) \; a_t \qquad (4)$$

C. *LSTM Model*

LSTM is a development of the RNN architecture used to solve the problem of gradient disappear/explode [40], which consists of a cell, input gate, output gate, and forget gate, where the cell stores values over an arbitrary time interval and the rest to control the flow. Information into and out of the cell.

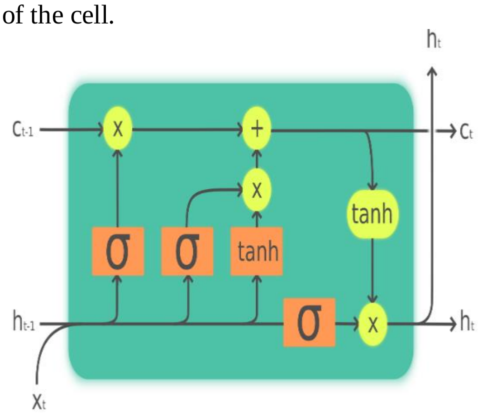

FIG 1: COMPONENTS AND CELLS LSTM

Where Xt represents the input at the time step t, ht is the output for a one-time step, and Ct is the additional dependency remembered from the previous time step added to the regular output.

D. ARIMA-LSTM Hybrid Model

ARIMA model is one of the traditional statistical models for predicting time series, which has accuracy on linear problems. Whereas LSTM has accuracy in capturing linear and non-linear dataset trends, the two models will be combined with their respective advantages in the first stage filtering linear output using ARIMA and non-linear trends using LSTM. ARIMA will make predictions first and continue using LSTM to predict the ARIMA prediction's residual value. The ARIMA-LTSM hybrid process uses equation [41] :

$$\epsilon_t = y_t - \hat{L_t} \quad (5)$$

$$\hat{y_t} = \hat{L}_t - \hat{N}_t \quad (6)$$

Where ϵt is the residual value of the ARIMA prediction, yt is the real data value, $\hat{L}\ t$ is the predicted value of ARIMA $\hat{N}t$ is the expected LSTM value.

III. METOD

A. Forecasting framework

The forecasting process is strongly influenced by the time-series data pattern produced, so an initial observation is needed to forecast. This process will analyze the type of data considering that each statistical method has different stages of work. Fig 2 shows the steps involved in the forecasting process.

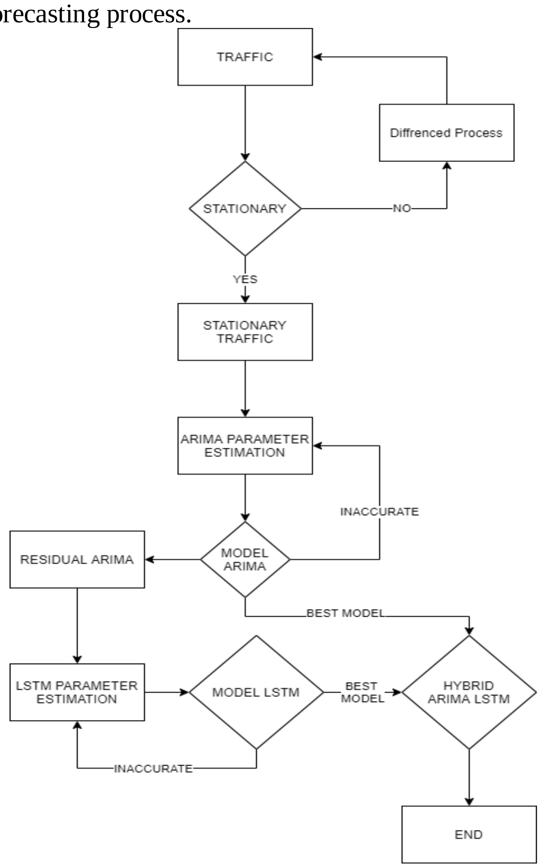

Fig 2: Process of ARIMA

In fig 2, the steps taken in the prediction process [3]: one of which is pre-processing the data using a time series histogram. The stationary test uses the Augmented Dickey-Fuller (ADF) unit root, one method for performing unit-root testing [37]. Second, when the data is not stationary, a differentiation process is carried out until the data becomes stationary.

They are third, modeling based on ACF and PACF analysis to obtain p, d, q values. Fourth, the parameters that have been received are diagnosed by evaluating the Root Mean Squared Error (RMSE) to obtain the best RMSE value. And Fifth, make predictions using the ARIMA parameters and models that have been obtained. In the process, the ARIMA model also produces residual value output. The value is processed in the future using the LSTM model with the Neural Network RNN architecture, which uses 100 LSTM units where the output of 100 LSTM units is combined into one value with the full connection. With the value of the ARIMA model to obtain the best predictive value.

B. Predicted Performance

Choosing the best model requires appropriate performance indicators in measuring the quality of the method or model, which can be assumed that the original data value is in yt, and the predicted value is yˆt.

This paper uses two evaluation indicators, namely the value of Mean Squared Error (MSE) and RMSE, whose equations are: [38] [39]

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(f_i - y_i)^2 \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \quad (6)$$

MSE is very good at giving an idea of how consistent the model is built. By minimizing the MSE value, it means minimizing the model variance. Models that have small variants can provide relatively more consistent results for all input data than models with large variants. In contrast, RMSE is an alternative method for evaluating the forecasting technique used to measure the accuracy of a model's forecasting results.

IV. BANDWITH FORECASTING

A. Data Set

The data used in this study are traffic from cells at the base transceiver station (BTS), where data was taken from 5-11-2019 to 30-01-2020 with 1-hour intervals where the attribute data is shown in Table 2. The data collection process This uses a query to the database, which is a storage area for traffic data from the BTS site

Table 2 Data Attribute

No	Date	Cell	Payload
1	5/11/2019 0:00	11	516.1843
2	5/11/2019 1:00	11	57.2152
3	5/11/2019 2:00	11	102.6939
4	………………..	…	……………
5	30/12/2019	11	1634.78

The plot model of the dataset can be seen in fig 3, which shows a graph plot of 120 hours or 5 days. The data set used was obtained by data providers. The data set collected the number of rows 2065, which we divide this data set into 3 parts, namely training data, validation, and testing.

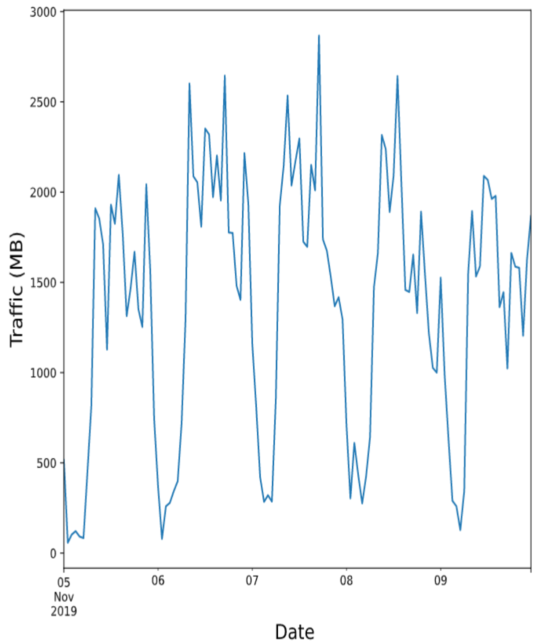

Fig 3: Data Set: 5-day view

B. Experimental results and analysis

The first step is pre-processing the data [43], which will be used using the describe () function in the Pandas library, which can be seen in table 3.

Table 3 Statistic Dataset

Variable	value
count	2064.000000
mean	1353.999429
std	745.253690
min	6.328000
25%	762.525000
50%	1399.685000
75%	1859.087500
max	4212.440000

In table 3, it can be observed that the dataset has 2064 rows, from the minimum value of 25%, 50%, and 75%, and Max indicates that the data has outliers so that the next step to detect outliers we use the box-plot in the matplotlib library can be seen in fig 4 the outlier value is valued above 3500 Mb.

At this stage, it can be seen in Fig. 5 that the histogram shows a right angle or positive slope. This is because the tail is from the point of distribution to the right and because it has a slope value greater than 0 (positive).

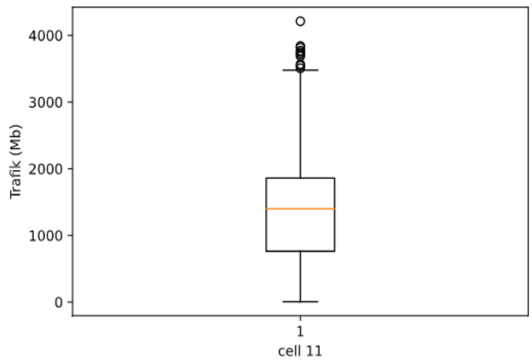

Fig 4: Plot Box-Plot

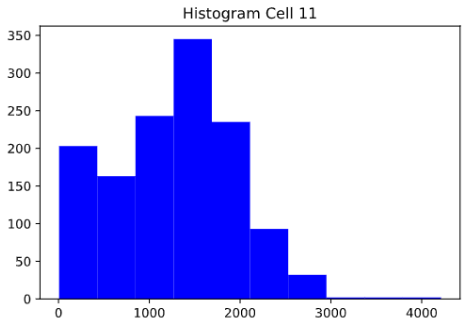

Fig 5: Histogram Traffic Cell 11

After knowing the data to be used shows a positive direction, then the stationary data checking process is carried out; In Table 3, it can be seen that the data to be used is stationary where the p-value is less than 0.5 and the Critical value is 1% smaller than the ADF value so that it can be concluded that the data to be used is stationary.

Table 3 Augmented Dickey-Fuller test

No	Variable		Value
1	ADF Statistic		- 13.837487
2	P-Value		0.000000
3	Critical Value		
		1 %	-3.435
		5 %	-2.864
		10%	-2.568

Next, perform an analysis with ACF and PACF, calculating the correlation between the data points in a series and the data points in a lag before the data points. This information then helps in calculating PACF [40] can be seen in Fig 6 and Fig 7 graph plot where the graph plot in Fig 6 shows a dying down pattern while in Fig 7 the pattern shown also shows dying down, so it can be said that this ARIMA model is the combination of AR and MA [42].

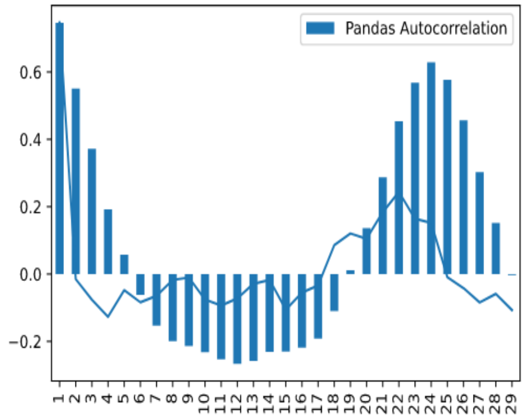

Figure 6 Auto Correlation Function

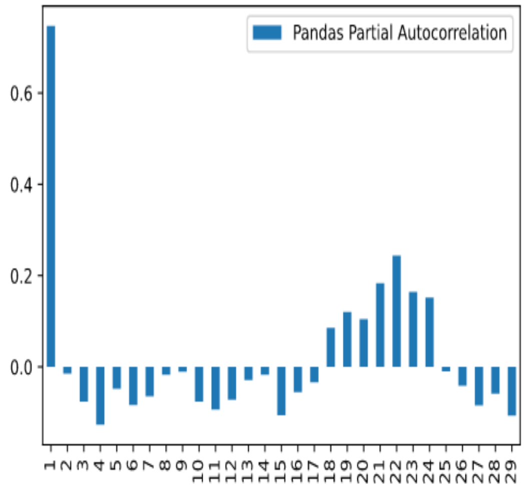

Fig 7: PartialAuto Correlation Function

The next step is testing with the ARIMA model, where the data is divided into 3, namely training, validation, testing with a composition of 60% training data and 20% data validation and testing, then testing the parameters p, d, q of the ARIMA. models (1.0.0), (1.1.0), (1.0.1), (0.0.1) and (0.0.6) and the results show the ARIMA / MA model (0.0.6) based on table 4 shows the best value of the forecast

Table 4 Comparison Model ARIMA

NO	AR	d	MA	Training (%)	Validation (%)	Testing (%)	MSE	RMSE
1	1	0	0	60	20	20	273451.9	522.9263
2	1	0	0	70	15	15	298748.0	546.5784
3	1	0	0	80	10	10	281976.5	531.0146
4	0	0	1	60	20	20	388260.1	623.1052
5	0	0	1	70	15	15	407318.5	638.2150
6	0	0	1	80	10	10	376059.4	613.2368
7	1	1	0	60	20	20	306330.1	553.4709
8	1	1	0	70	15	15	336050.0	579.6982
9	1	1	0	80	10	10	317705.7	563.6539
10	1	0	1	60	20	20	273732.6	523.1946
11	1	0	1	70	15	15	298799.7	546.6257
12	1	0	1	80	10	10	281958.0	530.9972
13	2	0	0	60	20	20	273791.7	523.2511
14	2	0	0	70	15	15	298824.0	546.6479
15	2	0	0	80	10	10	281961.4	531.0004
16	0	0	6	60	20	20	266782.2	516.5096
17	0	0	6	70	15	15	290450.6	538.9347
18	0	0	6	80	10	10	270783.1	520.3683

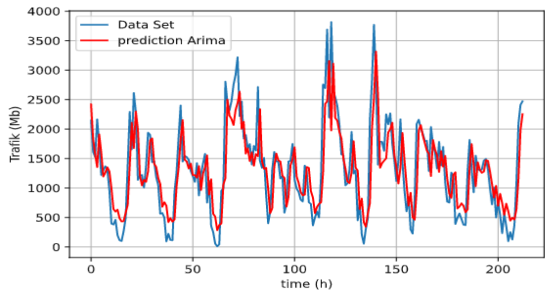

Figure 8 Arima (0.0.6) plot

It can be seen in fig 8 that the graph plot of the ARIMA prediction results with a value of 0.0.6 shows that the model is very good at making predictions where it can be seen that the prediction results shown in Figure 8 show the level of the prediction results is close to the validation data.

The next step after getting the best model from the Arima Model is the residual value of the ARIMA Model; then, it is reprocessed using the LSTM Model, where the LSTM model is tested so that the best Hybrid model results are obtained according to Table 5 Combination of Arima LSTM

The final results of the ARIMA-LSTM hybrid model can be seen based on table 5, where the combination of LSTM Windows 100, Layer 2, and Number of Neurons 100 produces the best RMSE value of 465.38866, better than the RMSE value of Arima's model 516.5096, in this result, the results are also obtained. The prediction is influenced by several parameters, one of which is the sliding windows, where the level of accuracy shown by the 100 sliding windows with 50 sliding windows is better. As is well known, sliding windows are applied as a step to smooth data and filter the high frequencies of the time series data components. Another parameter of the results obtained is the number of neurons where we tried to do several experiments using a value of 50-150, but the results we obtained showed the value of the results obtained when the neuron value was the same as the sliding window value, the prediction showed a better level of accuracy compared to the value of the results obtained—other parameter combinations.

Table 5 Combination Arima LSTM

NO	Windows	Layer	Neuron	Hybrid Model	
				MSE	RMSE
1	50	2	50	217607.52	466.48421
2	50	2	100	256293.93	506.25480
3	50	2	150	251105.16	501.10394
4	100	2	50	243871.12	493.83309
5	100	2	100	216586.61	465.38866
6	100	2	150	258923.87	508.84563

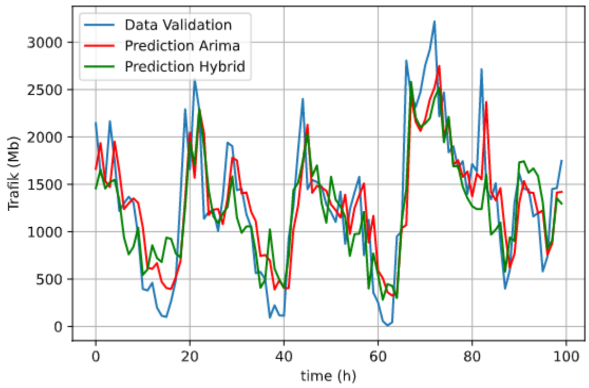

Figure 9 Plot Simulation Prediction

The simulation experiment in Figure 9 compares the Arima Method's prediction results and the combined method of Arima and LSTM, where the Arima method shown in red from points 0 to 100 shows the graph is almost close to real data. In contrast, the Arima LSTM method on the graph is green at time 0 - 10 it still shows inaccuracy, but time 20-100 this method shows accuracy where the time 20-23 and time 68 show the graph of the Arima lstm method is close to or equal to real data, the results of this analysis show the results of the Arima method. This lstm still shows some unfavorable prediction graphs even though, on the other hand, this method also shows the prediction results close to real data.

The Arima-LSTM hybrid model is then tested using test data which can be seen in Figure 10, which shows the accuracy of the predictions of the model.

Figure 10 shows the performance of the model that has been built using a combination of the Arima and LSTM methods; the accuracy of the prediction results shows a decrease in performance in the 50 hour period. So that the model built in this study is able to make accurate predictions for a period of 50 hours

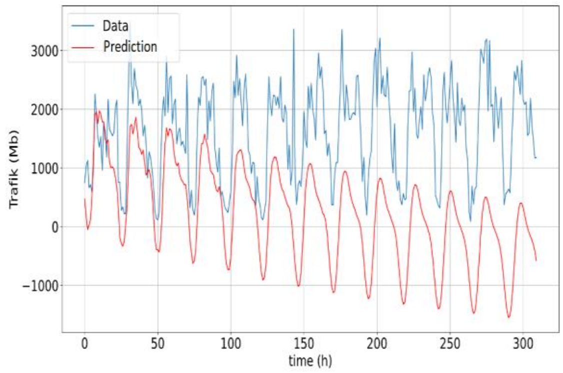

Figure 10 Prediction

V. CONCLUSIONS

In the implementation of forecasting in managing the amount of bandwidth in this study, we suggest using a combined method of ARIMA and LSTM RNN to predict the amount of traffic usage on BTS cells and test the forecasting results models using the MSE, RMSE method. In the combined ARIMA LSTM model, the accuracy of forecasting results is perfect. We get better RMSE results than the ARIMA model so that with this model, we can predict the network quickly based on historical network traffic data on BTS. But in the future, collecting more data from historical data can further increase the prediction time in the future, not only up to a period of 50 hours but can increase the prediction for 720 hours or 1 month. Currently, there are many factors that can affect the fluctuation of bandwidth requirements, the number of users, the bandwidth per user, the type of application, and the user's access time—the property, etc. Our goal is to examine how these factors affect traffic from the network as an additional parameter to the future model.

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