International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Modeling and Prediction LTE 4G NW According to Memory Algorithm of Long-Short Term

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Submitted: 17/10/2022 **Accepted**: 06/01/2023

Abstract: With increasing of using smart phone, has run to a tense growing in internet traffic. Therefore, prediction and modeling NW turn to be very significant for monitoring NW for increasing quality of services (QoS). The novelty of designed prediction model for managing the NW intelligently. In this paper, proposed Long-Short Term Memory (LSTM) to forecast traffic as cellular. The normalization as min-max method has been implemented for scaling the NW traffic NT data. The LSTM model was evaluated by employing real standard LET NW loading that gathered from kaggel. The empirical results of LSTM model have revealed that has achieved greater accuracy, according to R metrics 98.67% at the training phase. The prediction NT was very close to the target values, this is approved the robustness of the deep learning model LSTM for handling LET traffic. Where the proposed system at unseen data (testing phase) has achieved superior performance, the correlation percentage of the LSTM model at testing phase is 97.95%. Finally, we believe that the system has ability to monitoring LET NW.

***Keywords**: Long-Short Term Memory, Deep learning, 4G NW, time series model, Prediction NW*

1. Introduction

Internet is NWs (NW that) connect billions of Internet utilizers and hosts and carries huge (Terabytes) data across the worldwide backbone [1-3]. International Union of Telecommunication has forecasted in the beginning of 2015 that three billion utilizers will be linked to Internet \cite {report_2014}. Internet has a giant optical fibers infrastructure, copper wireless and wires connections which are used by packet switches for connecting an extensive end-hosts variety of a range from customary web servers, laptop computers and PCs, to a large cell phones number and devices being smaller inserted in our homes, in the surroundings around us and in cars. Furthermore, Internet is as well infrastructure which maintenances a services variety i.e., mail, web, sharing of file, radio, telephony, games, TV and video distribution, banking of many kinds and commerce and in which new applications continually are deployed and developed [4-5]. NW infrastructure is growing at a rapid pace thus; Internet has become a very complex system. Due to this NW and consistancy of having an independent and smaller NW of huge number, and as well protocols which define how communication of Internet is carried out and how it is organized into layers with diverse roles. Internet is a NW of heterogeneous set that interlinked with various capacities and sizes and at various administrations. NW as thousands which set up Internet is linked together in hierarchy being loose. The NT prediction is a significant subject which has recently received ample attention from the community of computer NW [6-8]. The NT prediction duty, one of the classic subjects in measured data based NW control is for forecasting the variation of future traffic and it can be regarded as a time sequences prediction issue. The NT several works prediction in literature review are concerned in problem solving to improve the NT effectiveness and efficiency monitoring via in advance forecasting the flow of information packet. Thus a prediction as precise traffic model must have the capability for capturing the characteristics of prominent traffic, i.e., long and short-range dependence, similarity being self [9]. More accurately in order to predict NT models, it needs on 2 chief parameters: the getting of preceding NT data and to what extent forecasting future NW with traffic process rate able to predicted for a particular error limitation. The main contribution of the proposed research is as follows:

1. Using advance artificial intelligence like deep model of learning LSTM for prediction the NT.
2. The model being suggested was tested using real Long Term Evolution (LTE)
3. The system able to be utilized nay application of real time for forecasting values of future.

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2. Background of study

Within the collected works, first paintings hiding place website traffic site predictions for switching circuit through growing time as statistical collection fashions based totally on records of observation i.e., auto-regressive moving integrated averages (ARIMA) [11,12]. Additional, numbers of models of prediction are utilized to take care of packets loading traffic expect with increase time collection models primarily according to artificial expertise through the cell NW utilize [13, 14]. Time series models (TSM) number was brought to predicte momentary traffic (sec, min) by way of using deep leaning [15, 16]. A few designed the model for predicting radio frequency plans making [17]. TSM have been carried out to be expecting loading web page traffic in NW of telecommunication, within the preceding research, visitors of circuit-switching forecasting is tackled by means of manner of developing by using the usage of first rate statistical TSM primarily according to test information. Conventional TSM i.e., vehicle ARIMA anticipated momentary NW web page traffic demand, SARIMA and ARIMA being seasonal utilizeded for seasonal traffic prediction [18] and few utilized smoothing algorithm as exponential (holt–winters) [19,20], for coming across seasonal and method in call for traffic. The specialists have prolonged the linear model of time collection ARIMA for generalizing conditionally vehicle regressive heteroskedastic (GARCH) [21], to be expecting dependencies of lengthy-range.

Qiu et al. [22] proposed hybrid a wavelet-based deep studying framework for predicting the variety of clients associated with mobile NW. Used linear regression (arima) [23].

Presently, strengthen time collection models had been utiliz to expect cellular NT, implemented bayesian regression as linear [24], superior studying system [25], support vector regression (SVR) to expect mobile traffic[26], by using artificial neural NW (ANN) for forecasting NT [27-29]. Chen et al. [30] employed regression model to predict every day tourist traffic. Further, SVR model executed to predict toxicity evaluation [31], developing model to predict battery life [32,33], using time series model to predict chemical [34,35], in additional, TSM were applied to predict financial [36,37], and growth agricultural manufacturing with the aid of the use of the usage of prediction model [38-40].

3. Methodology

Formwork to developed system of intelligence to forecast 4G mobile NT is presented in Fig. 1.

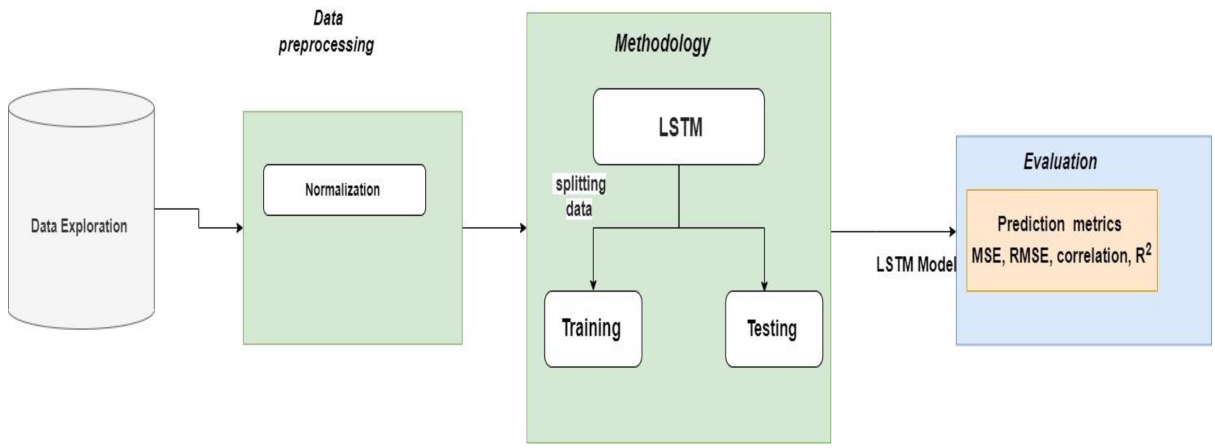

Fig. 1. Suggested system

3.1Dataset

Proposed system was evaluated using LTE 4G NW traffic, collected from Kaggle. The characterize of the 4G NW form radio transmitter to serve the computer. The 4G data simple is presented in table 1, the dataset is available in the public link https://www.kaggle.com/naebolo/predict-traffic-of-lte-NW

Table 1. Training dataset

Periods	Simples
October 2018	45335

3.2Normalization Method

Normalization of min-max method was employed for scaling the NT into format being simple, the method was scaling the data tin to [0,1].

$$z_n = \frac{x - x_{min}}{x_{max} - x_{min}}\left(New_{max_x} - New_{min_x}\right) + New_{min_x}$$

(1)

Where,

the x_{min} :the minimum of mobile NT

x_{max} :maximum of mobile NT.

New_{min_x} :minimum value 0 and

New_{max_x} :maximum value 1.

3.3 Prediction Model

LSTM model was applied to prediction mobile NT data. LSTM is kind of recurrent neural NW (RNN) used for predicting NW traffic. The LSTM is feedback connections, it is implemented in many real life applications [41-44].

$$f_t = \sigma\left(w_f[h_{t-1}, x_t] + b_f\right)$$

(2)

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i)$$

(3)

$$\widetilde{C}_t = tanh(w_C[h_{t-1}, x_t] + b_C)$$

(3)

$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t}$
(4)
$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o)$
(5)
$h_t = o_t * \tanh(C_t)$
(6)
Where:
i_t: input gate
f_t : foreign gate
o_t : output gate
h_t: hidden layer
$w_f, w_o\ w_c$. : weighted neural NW
C_t : internal memory cell
b_f and b_o: bias of neural NW
xt: training data

The important parameters values of model of LSTM is shown in table 2.

Table 2. Parameter LSMT values

Parameters of LSTM algorithm	
Hidden layer. No	8
Epochs No.	20
Number of Batch Size	500
Iterations	200
Delays	[1,7,9]
Optimizer function	Rmps

F. Model Evaluation Criteria

Performance measurement to analysis the LSTM model is used; we have applied three metrics like (MSE), (RMSE), Correlation (R) and (MAE).

$$MSE = \frac{1}{N}\sum_{k=1}^{n}(x_t - \bar{x}_t)^2 \quad (7)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{n}(x_t - \bar{x}_t)^2} \quad (8)$$

$$R\% = \frac{n(\sum_{i=1}^{n} y_{i,exp} \times y_{i,pred}) - (\sum_{i=1}^{n} y_{i,exp})(\sum_{i=1}^{n} y_{i,pred})}{\sqrt{\left[n(\sum_{i=1}^{n} y_{i,exp})^2 - (\sum_{i=1}^{n} y_{i,exp})^2\right]\left[n(\sum_{i=1}^{n} y_{i,pred})^2 - (\sum_{i=1}^{n} y_{i,pred})^2\right]}} \times 100 \quad (9)$$

Where, x is NT , $\bar{x}_t$ is prediction values and N is loading LET traffic.

4. Results analysis

In this part, the empirical LSTM model results were presented for prediction LET 4G NW. The LET 4G NW dataset was collected in three moth time period. In order to format and scaling NT data employing Min-max normalization method. For validation LSTM model the 4G dataset was separated into 30% for data testing and 70 % for training.

4.1Training phase of LSTM model

Seventy % of the 4G mobile traffic dataset was utilized for training process, Table 3 demonstrations the LSTM findings for prediction values. It is noted the values of prediction are so close to loading NT. The prediction LSTM values in training phase with respect o the evaluation metrics are MSE=0.021846, and RMSE=0.1478.

Table 3. SES-LSTM performances model in the testing phase.

Time interval	MSE	RMSE	Error Mean	R %
October 2018	**0.021846**	**0.1478**	**0.00149**	**98.67**

Figure 2 shows the output of LSTM model in train phase, the graphical represented the time series plot and error values of LSTM model from training phase.

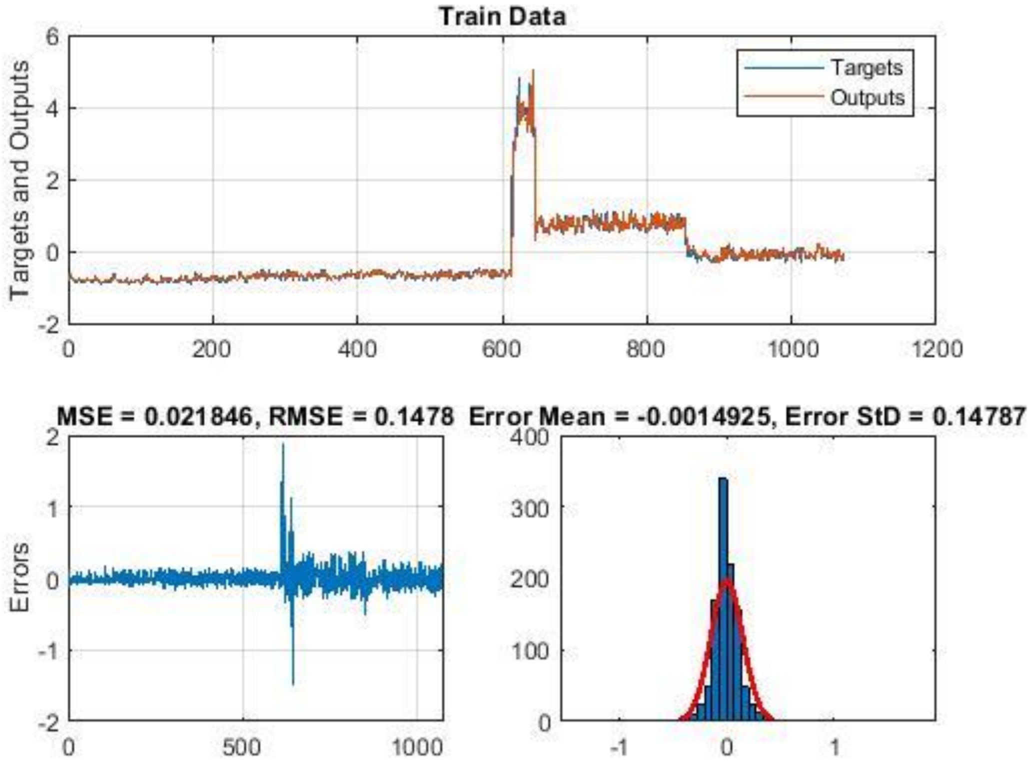

Fig. 2. Performance of LSTM model for predicting LET NT at training phase.

The regression plot of LSTM model in training phase is presented in figure 3, While the target (x-axis) traffic values represents target values of LSTM model, the LSTM output model is represented in (y-axis). It is observed that forecast errors very less by using evaluation metrics like MSE, RMSE and R. The graphic representation I used to finding to association between the future traffic values and the values of target by employing the Pearson's correlation.

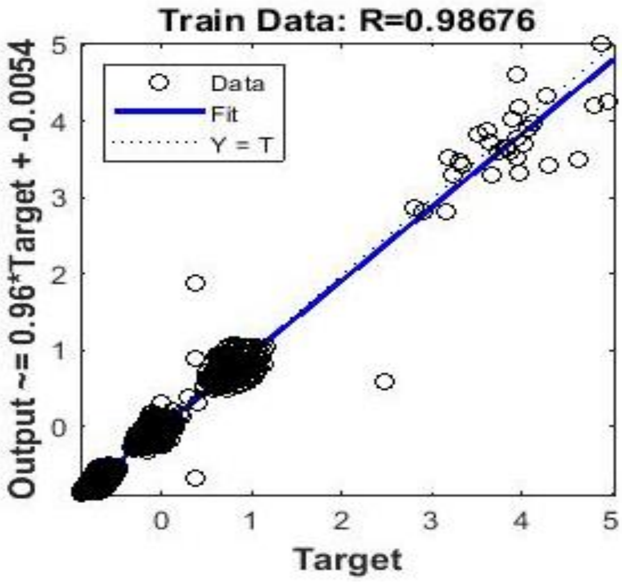

Fig. 3. Regression of LSTM mode at training phase

4.2 Testing phase of LSTM Model

The testing phase is very important for validating the LSTM model, the validation phase is predicted the 4G NW data without seen the data. We have splitting 30% from data for forecasting future NT. Table 4 summarizes the prediction values of LSTM model in testing phase, it is noted that prediction errors are very close in testing phase where MSE=0.06539.

Time periods	MSE	RMSE	Error Mean	R %
October 2018	**0.06539**	**0.25575**	**0.0866**	**97.95**

Figure 4 illustrates plot of time series for forecasting LSTM mode in phases of testing to predicte 4G NT.The prediction error of LSTM model in testing phase was satisfied. It is observed that error std 0.24109. The prediction LSTM errors of the model are 0.086.

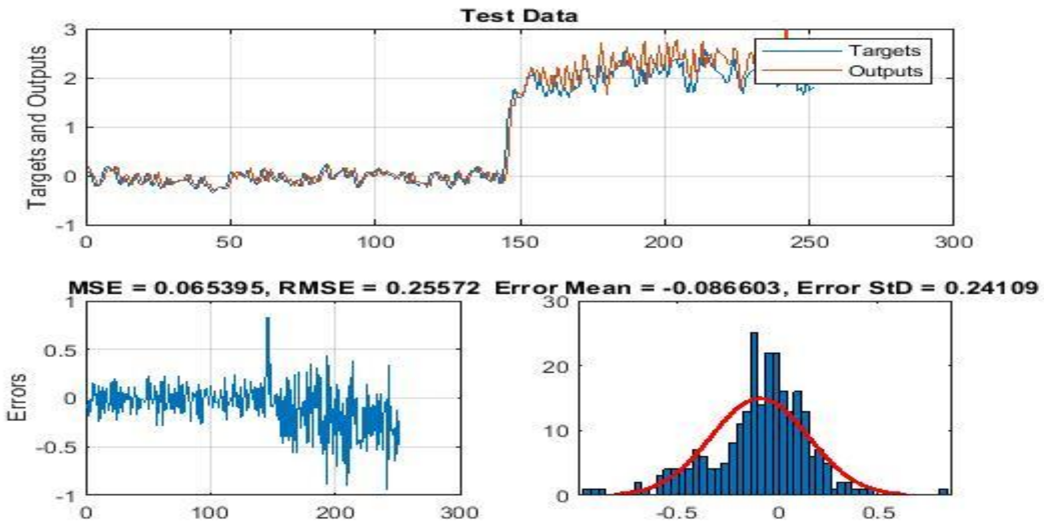

Fig. 4. LSTM model performance to prediceLET NT at phase of testing.

Fig. 5 displays the regression LSTM plot model in testing phase, where *target* (x-axis) uses to representation the target traffic values, the *output* (y-axis) prediction values. Experiment results of LSTM model in testing phase that is revealed the efficiency of the LSTM model. It is observed that the correlation percentage is 97.95% in testing phase.

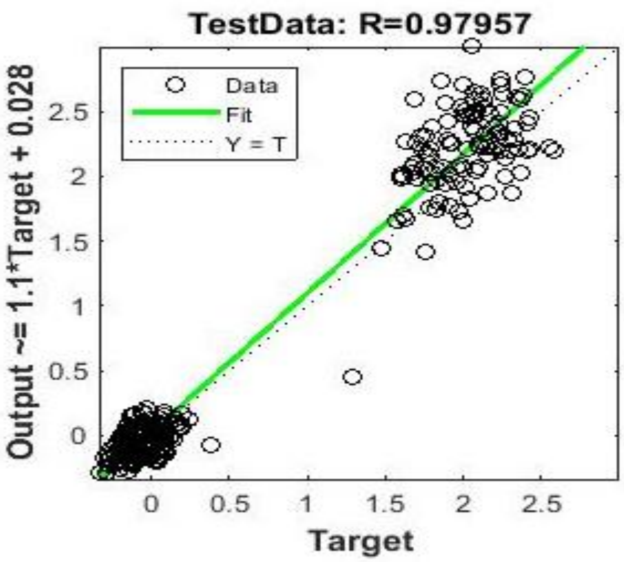

Fig. 5. Regression of LSTM mode at testing phase

5. Conclusion

Cellular LET 4G NW modeling and predicting play significant role for monitoring and manage the performance of mobile NW. Therefore, modeling LET 4G NW has become a vital part for assistance telecommunication for increasing the quality of service like packet loss, bandwidth control and avoids congestion. In this research study, LSTM model is presented to forecast Cellular LET 4G NW. The proposed system is used to measure LET 4G NW behaviours for improving the enhance Service Quality (QoS) of 4G NW by using machine intelligence to forecast future NW. Developed deep learning model like LSTM is our novelty for improving traditional system to obtain accurate forecasting values. The results of LSTM model have achieved superior forecasting results. We can trust that LSTM model can be used for any real time series applications.

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