Bulletin of Electrical Engineering and Informatics
Vol. 14, No. 3, June 2025, pp. 1820~1829
ISSN: 2302-9285, DOI: 10.11591/eei.v14i3.9221

Deep learning-based cellular traffic prediction for 4G long-term evolution networks using three models

Hassnaa Shindou, Yassine El Hasnaoui, Srifi Mohamed Nabil
Laboratory of Advanced Systems Engineering, Ibn Tofail University, Kenitra, Morocco

Article Info

Article history:

Received Aug 30, 2024
Revised Dec 30, 2024
Accepted Mar 9, 2025

Keywords:

4G long-term evolution network
Artificial intelligence
Mobile traffic
Traffic load prediction
Quality of service

ABSTRACT

Wireless networks can be seen as the essential element of contemporary communication systems, connecting, in one way or another, billions of people and technologies all over the world. As a result, there is more of requirement from the area of application for models, which should be able to help in the analysis of the time series of mobile traffic to enhance the quality of service (QoS) in the present networks as well as in the future ones. The primary objective of this article is to develop effective artificial intelligence (AI) models for traffic load prediction in cellular networks. To achieve this, we employ three models; gated recurrent unit (GRU), bidirectional long short time memory (BiLSTM), and long short time memory (LSTM), to make numerical estimates of the network traffic at 4G long-term evolution (LTE) cell towers. The empirical results indicate that the BiLSTM model outperforms both the LSTM and GRU models, achieving root mean squared error (RMSE), mean absolute error (MAE), and R2 values of 86.64, 67.12, and 93.23%, respectively. Although this research focuses on traffic modeling for 4G LTE networks, the proposed models hold significant value for the development and optimization of the upcoming generations.

Corresponding Author:

Hassnaa Shindou
Laboratory of Advanced Systems Engineering, Ibn Tofail University
BP 241, 14 000 Kenitra, Morocco
Email: hassnaa.shindou@uit.ac.ma

1. INTRODUCTION

In the management of cellular networks, accurate simulation and prediction of load are essential for achieving high resource utilization. This research proposes a novel approach that leverages artificial intelligence (AI) methods to forecast traffic loads on cellular networks, specifically focusing on long short time memory (LSTM) [1], bidirectional long short time memory (BiLSTM) [2], and gated recurrent unit (GRU) [3] models for predicting network traffic at 4G long-term evolution (LTE) cell towers. Effective traffic management is increasingly critical in today's data-driven environment, particularly with the rapid expansion of 5G technology [4]. Predicting both 4G LTE and 5G traffic is vital for enhancing quality of service (QoS) and involves sophisticated algorithms, including linear regression, support vector machine regression, and deep learning techniques like LSTM, BiLSTM, GRU, and convolutional neural networks (CNN) [5]-[8]. Accurate traffic predictions facilitate better network planning, bandwidth provisioning, and traffic engineering, enabling more efficient data flow management and deeper insights into network characteristics. As technology continues to evolve, effective traffic modeling will unlock new opportunities across various sectors, underscoring the necessity for secure, reliable, and efficient systems. Various methodologies, including genetic algorithms, artificial neural networks (ANN), and fuzzy logic, have been explored to enhance traffic prediction and network management. Deep learning models, such as deep neural networks (DNN) and recurrent CNN, have also been employed to forecast traffic flow [9]-[13].

Previous studies have highlighted the potential of combining traditional and advanced methodologies. For instance, Alsaade and Al-Adhaileh [10] proposed a model integrating single-exponential smoothing with long short-term memory (SES-LSTM), achieving R-squared values of 88.21%, 92.20%, and 89.81%. Similarly, research by Kurri *et al.* [9] utilized an LSTM model to analyze a year's worth of traffic data from 4G LTE cell towers, yielding R-squared scores between 0.5014 and 0.54233, indicating a 9.6% to 17.7% improvement over the ARIMA model. Despite these advancements, challenges persist in capturing the complex and dynamic nature of network traffic patterns, highlighting the need for continued development of predictive models. The proposed model demonstrates superior performance in predicting network traffic relative to existing methods, enhancing accuracy, optimizing resource allocation, and ensuring a higher QoS [14]. Ultimately, this innovation aims to improve the user experience in an increasingly demanding mobile communications landscape.

In summary, more precise models and predictions of network traffic patterns are crucial for ensuring better QoS and improved network traffic management [15]. This paper introduces a model that enhances traditional time-series approaches and utilizes various types of network data concurrently, providing the most suitable bandwidth allocation for optimal network utilization. The major contributions of this research include the development of an intelligent system capable of accurately predicting cellular and LTE network traffic, significantly enhancing prediction accuracy and establishing a robust framework for future network management. The following sections will detail the methodologies employed, compare the performance of the proposed model with existing ones, and critically discuss the implications of the findings. These insights are expected to be valuable for industry practitioners and researchers alike, paving the way for advancements in network traffic management across various fields, such as data prediction, network optimization, and capacity planning.

2. MATERIALS AND METHODS

This section gives the details of the materials and methods to be used in the proposed model which is outlined in Figure 1. provides Proposed traffic prediction model which is intended for increasing the efficiency of the models of time series for the prediction of network traffic. The advancements in this study have fine-tuned the deep learning techniques namely: GRU, LSTM, and bidirectional LSTM for time series analysis. The real network data was used in order to evaluate the performance of the proposed models. The data is first pre-processed through a process of resampling on an hourly level and includes a SES layer the range of values is scaled between 0 and 1 [14], [16]. The scaled data is partitioned into the training set and the testing set, with the former comprising a dataset collected up to the week prior to the final week of data and the latter comprising of data from the final week only. The training data is then utilized for the creation of time series sequences and the time step we consider is 24 hours and these are used in the training of the models.

The GRU model is initialized with three layers of the GRU and has a linear activation output layer as well as compiled with the Nadam optimizer and mean squared error loss functions [14], [17]. The LSTM model is specified with three LSTM layers and a dense output layer; it is compiled with the Nadam optimizer and mean squared error loss function. Bidirectional LSTM model is defined with three bidirectional LSTM layers and dense output layer The defined model is compiled with Nadam optimizer, and mean squared error as loss function [2] as shown in Table 1. The loss values for the training and testing sets are plotted for all three models, and the predictions are made on the test set [17]. Finally, the predicted values are scaled back to their original values and plotted against the actual values for comparison.

2.1. 4G cell traffic datasets

The utilization of authentic datasets comprising of actual network traffic traces is crucial in assessing and validating the efficacy and efficiency of the proposed model's performance. The dataset we gathered from Kaggle includes packet data specifically from 4G cell networks. The data flow from mobile service users is referred to as 4G cell traffic; the mobile device will be provided by a nearby 4G cell networks. For about a year, data is collected in 57 cells at 1-hour intervals in an LTE network. Data is gathered in an LTE network. In the current study, we examined the proposed system using one year of data from cell 000113. The public dataset is available at website Kaggle [4], [10], [11].

2.2. Simple exponential smoothing

SES models stand out as one of the most widely utilized and fundamental prediction methodologies, owing to their effectiveness and pervasiveness in predictive modelling [16]-[18].
The equation for SES is (1):

$$S_{t+1} = \alpha * Y_t + (1-\alpha) * S_t \quad (1)$$

In the given equations, S_{t+1} represents the forecast for the next time period, Y_t new observation (or actual value) in period t, S_t is the forecast for the current period and α presents smoothing parameter, a value between 0 and 1 (0<α<1).

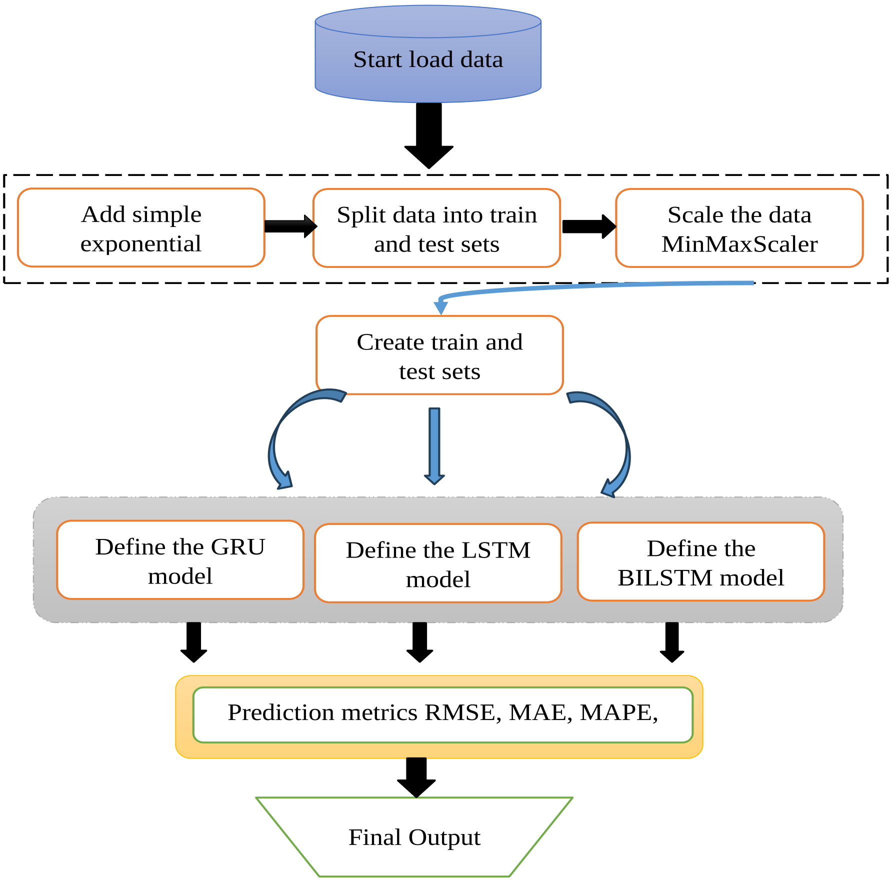


Figure 1. Proposed traffic prediction model of GRU, LSTM, and BiLSTM

Table 1. Hyperparameters for training: LSTM, BiLSTM, and GRU

Parameter names	Numbers
Initial learning rate	0.002
No. of epochs	100
batch_size	64
Optimization algorithm	Nadam
Loss function	MSE
LSTM hidden layers	3
Timesteps	24

2.3. Normalization

MinMaxScaler is a technique used to normalize data by adjusting it to fall within a specific range. In the context of LTE network traffic prediction, where the data is complex and made up of signals with varying characteristics, this scaling is essential. It ensures that larger numerical values don't overshadow smaller ones. By rescaling the data with MinMaxScaler, we can improve the accuracy of predictions and speed up processing. The scaler works by transforming the data to a range between zero and one. This approach offers two main advantages: it prevents data with larger values from dominating and helps avoid numerical issues during prediction. The transformation using MinMaxScaler is achieved by removing the feature's minimal value and then dividing by the feature's range (i.e., maximum minus minimum). This ensures that the data is rescaled to fit within the specified range while preserving its relative distribution [14], [19], [20].

The equation for MinMaxScaler is given by (2):

$$f\_scaled = \frac{(f - f_{min})}{(f_{max} - f_{min})} \quad (2)$$

where f denotes the feature value, this equation scales the feature values between 0 and 1. The resulting scaled values can be interpreted as the relative position of the original value within the range of the feature, f_{min} and represent respectivelly the feature's minimum and maximum values.

2.4. Gated recurrent unit

GRUs belong to the category of recurrent neural networks (RNNs) that are extensively employed in natural language processing and other sequence modeling applications. A GRU cell has an internal state vector that can be updated based on the current input and the previous state. For a given input time series y_t at time, the equations for a single GRU cell are respectively reset gate, update gate, memory and final output as (3)-(6):

$$r_t = \text{sigma}\left[\left(W_{ry}y_t\right) + (W_{rh}h_{t-1}) + b_r\right] \quad (3)$$

$$z_t = \text{sigma}\left[\left(W_{zy}y_t\right) + (W_{zh}h_{t-1}) + b_z\right] \quad (4)$$

$$\widetilde{h_t} = tanh\left[\left(W_{hy}y_t\right) + (W_{hh}(r_t \odot h_{t-1})) + b_h\right] \quad (5)$$

$$h_t = \left[\left(z_t \odot \widetilde{h_t}\right) + ((1 - z_t) \odot h_{t-1})\right] \quad (6)$$

The parameters of a GRU include:

In this context, r_t and z_t are the parameters for the reset and update gates, respectively, while sigma denotes the sigmoid activation function. The variable h_{t-1} refers to the output from the previous GRU unit, and $\odot$ signifies element-wise multiplication. The weight matrices W_{rh}, W_{ry}, W_{zh}, W_{zy}, W_{hh}, and W_{hy} are linked to different inputs, with biases b_r, b_z, and b_h associated with each gate's activation. The candidate hidden state $\tilde{h}_t$ is computed using (3), This equation describes how the candidate hidden state $\tilde{h}_t$ is derived by applying a hyperbolic tangent function to the weighted sum of the reset gate-modified previous hidden state and the current input, plus the bias term b_h [1], [3], [21], [22].

2.5. Long short time memory

LSTM is a powerful type of RNN which is used mainly for issues connected with sequence prediction. LSTM networks have the capacity to store past information in their loops and they tend to use this information in order to forecast future events. This makes them useful for a wide range of applications such as; speech recognition, natural language processing, and time series prediction.

There are several essential components in the foundation of an LSTM cell, called gates that define how information is dealt within the network. The forget gate G_t decides which parts of the previous cell's memory should be kept or discarded, allowing the network to forget irrelevant information. The input gate i_t controls how much new information from the current input should be added to the cell's memory. The candidate memory state $\widetilde{M_t}$ represents potential new information that could be integrated into the cell's memory. These gates work together to update the cell's memory state M_t, combining what's remembered with new information. The output gate O_t then determines what part of this updated memory should be passed on to the next step as the hidden state h_t.

$$G_t = sigma[\, b_g + \left(U_{hg}\, h_{t-1} + U_{yg}y_t\right)] \quad (7)$$

$$i_t = sigma\, \left[b_i + \left(U_{hi}\, h_{t-1} + U_{yi}y_t\right)\right] \quad (8)$$

$$\widetilde{M_t} = sigma[U_{hm}h_{t-1} + U_{xm}y_t + b_m] \quad (9)$$

$$M_t = \left[(G_t * M_{t-1}) + \left(I_t * \widetilde{M_t}\right)\right] \quad (10)$$

$$O_t = \text{sigma}[U_{ho}h_{t-1} + U_{xo}y_t + b_o] \quad (11)$$

$$h_t = [O_t * (tanh(M_t))] \quad (12)$$

In these equations, G_t, i_t, and O_t denote the parameters for the forget, input, and output gates. The weight matrices U_{hg}, U_{yg}, U_{yi}, U_{hi}, U_{hm}, U_{xm}, U_{ho}, and U_{xo} connect the previous hidden state h_{t-1} and the current input y_t. The biases b_g, b_i, and b_o adjust the gate functions, while the sigmoid function "sigma" regulates the activation [1], [12], [22], [23].

2.6. Bidirectional long short time memory

BiLSTM is a RNN that is composed of several LSTM layers that can process input sequences in both forward and backward orientations. A typical LSTM processes the input sequence in only one way, from beginning to finish; however, a BILSTM may access information from both the past and future contexts at the same time, allowing it to capture more complicated relationships within the input sequence. BiLSTM is widely employed in applications including natural language processing, time-series analysis and speech recognition, where the ability to capture contextual dependencies in both directions is critical for successful prediction or classification [2], [12], [24].

2.7. Model evaluation criteria

To evaluate how well the predictive models perform, we use several key metrics: root mean squared error (RMSE), which tells us how much the predictions differ from actual values on average by measuring the square root of the squared errors; mean absolute error (MAE), which looks at the average of all absolute differences between predictions and actual results; mean absolute percentage error (MAPE), which shows the prediction accuracy as a percentage; and R2, which indicates how well the model's predictions match the real data. By considering all these metrics, a thorough examination of the performance of the proposed predictive models can be obtained. The proposed models include LSTM, GRU, and BiLSTM, which are all commonly used deep-learning architectures for time-series prediction [17], [19], [21], [24]-[27].
The equations for the evaluation metrics commonly used in predictive modelling:

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(x_t - \widehat{x_t})^2} \tag{13}$$

Spearman's correlation coefficient (R):

$$R^2 = 1 - \left(\frac{\sum_k (x_t - \widehat{x_t})^2}{\sum_k (x_t - \overline{x_t})^2}\right) \tag{14}$$

$$MAE = \frac{1}{N}\sum_{k=1}^{N}|x_t - \widehat{x_t}| \tag{15}$$

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{x_t - \widehat{x_t}}{y_t}\right| * 100\% \tag{16}$$

2.8. Proposed traffic prediction model

The proposed model predicts time series data using different types of RNN such as LSTM, GRU, and bidirectional LSTM. The data is resampled to hourly frequency and SES is applied to one of the columns. The data is then split into training and testing sets and normalized using MinMaxScaler [6], [14]. A function is defined to create training and testing sets for LSTM, BiLSTM, and GRU models [24], [27]. The GRU, LSTM, and Bidirectional LSTM models are defined and compiled with appropriate parameters, and then trained on the training data. The model's history is saved, and its performance is evaluated using RMSE, MAE, MAPE, and R2 on the test data [17], [19], [21], [25]-[27]. Finally, the trained models are stored for future use.

3. RESULTS AND DISCUSSION

In this study, we compared the performance of three deep learning models LSTM, BiLSTM, and GRU using four evaluation metrics: RMSE, MSE, MAPE, and R² as shown in Figure 2. The results we obtained clearly demonstrate that the BiLSTM model outperformed both LSTM and GRU across all metrics, indicating its superior ability to predict cellular network traffic. As summarized in Table 2, the evaluation for each model based on RMSE, MSE, MAPE, and R2 shows BiLSTM's consistently better performance. These results confirm that BiLSTM offers a more accurate prediction of network traffic compared to the other models. When analyzing the results in detail, it becomes evident that BiLSTM's ability to capture long-range dependencies within the time-series data contributes to its improved accuracy. The lower RMSE and MSE values indicate that BiLSTM is better suited for reducing the prediction error compared to LSTM and GRU. Additionally, the R2 values further support these findings, demonstrating how well each model's predictions correlate with the actual data. In fact, BiLSTM achieved an R2 of 93.23% as indicated in Figure 2(a), indicating a stronger fit to the observed data. Compared to the LSTM model, which had an R2 of 92.75% as shown in Figure 2(b), BiLSTM showed a significant improvement. This improvement can be attributed to its bidirectional structure, which allows it to process the input sequence in both forward and backward directions. On the other hand, the GRU model also performed well but did not reach the same level of accuracy as BiLSTM, with an R2 of 92.93% as represented in Figure 2(c). While BiLSTM exhibited superior performance, it is important to highlight that this study focused on cellular network traffic data, which may have specific characteristics that benefit from BiLSTM's bidirectional nature. However, this comes at the cost of higher computational requirements compared to LSTM and GRU. The findings suggest that BiLSTM is a more robust option for predicting cellular traffic load, especially in situations where precise predictions are critical to maintaining QoS. Additionally, hybrid models that combine BiLSTM with other advanced techniques, such as attention mechanisms or convolutional layers, could further improve prediction accuracy and reduce computational costs. Our findings align with previous research that highlights the advantages of different models like ARIMA, LSTM, and others in time-series prediction tasks. Studies have shown that BiLSTM tends to capture temporal patterns more effectively than LSTM and GRU models, particularly in scenarios where bidirectional information enhances predictive performance. However, it is essential to note the trade-off in computational cost, which must be considered when applying these models to practical applications.

Table 2. Three models performance

Model	RMSE	MAE	MAPE	R2
GRU	88.5177	70.0329	7.7678	0.9293
LSTM	89.6233	70.2797	7.8027	0.9275
BiLSTM	86.6494	67.1269	7.4331	0.9323

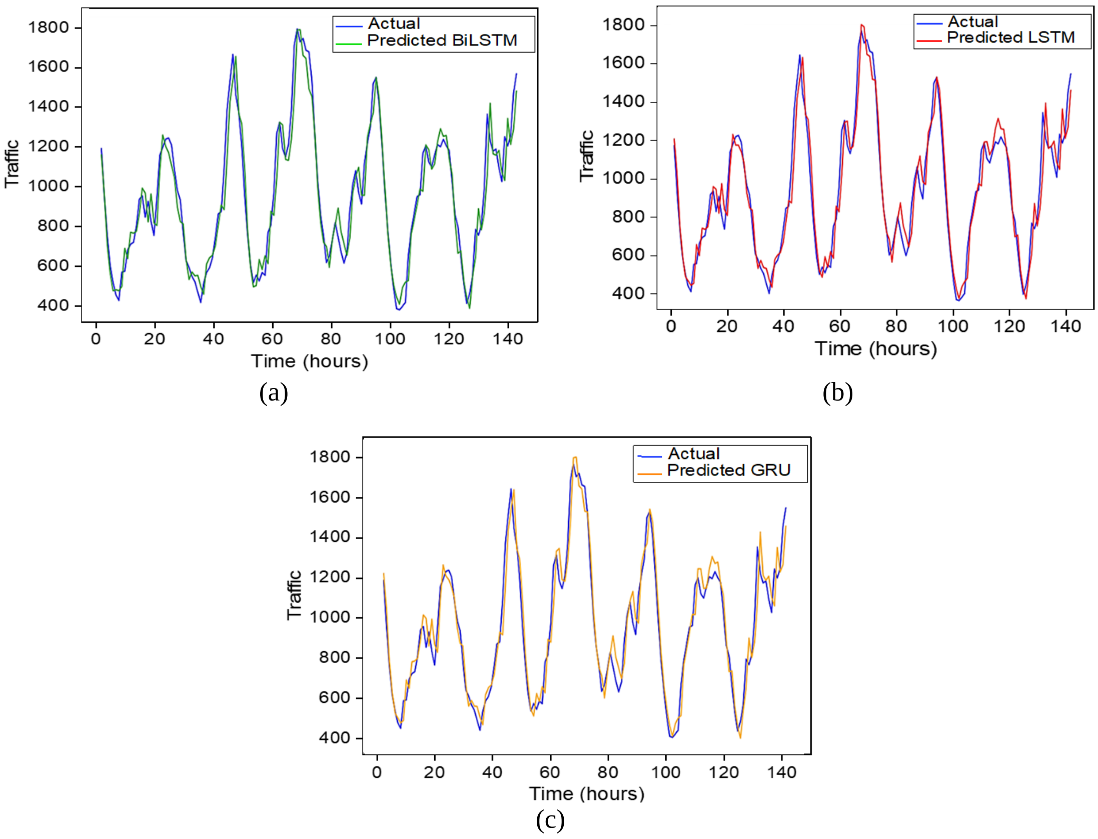
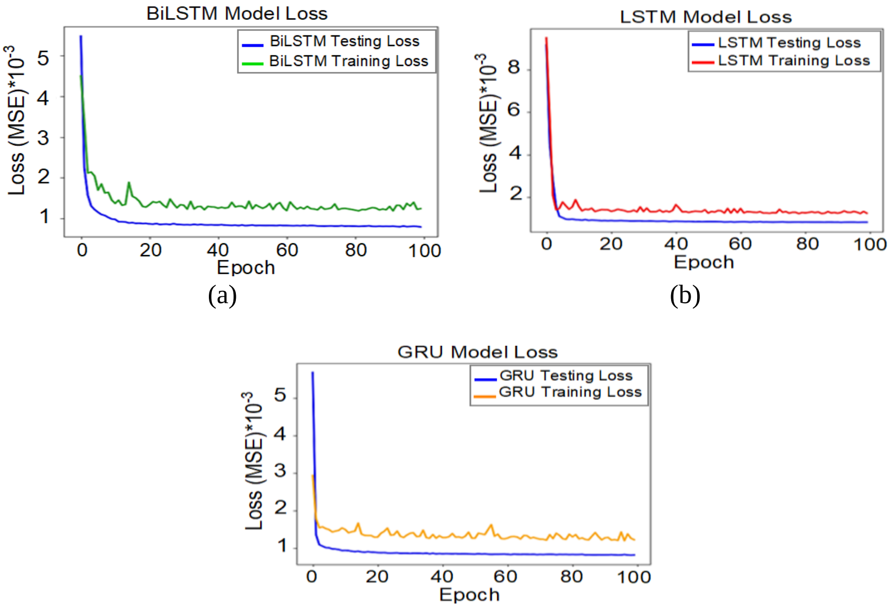


Figure 2. Predicted vs actual traffic: a comparative evaluation of; (a) BiLSTM, (b) LSTM, and (c) GRU

In conclusion, the experimental results demonstrated that BiLSTM outperforms LSTM and GRU in terms of RMSE, MSE, MAPE, and R^2, making it the most appropriate model for cellular traffic prediction in this study. Its ability to minimize prediction errors, while maintaining a high correlation with actual traffic data, indicates its potential as an optimal solution for network traffic forecasting.

The consequences display the very last loss and minimal loss for three models (GRU, LSTM, and BiLSTM) educated on a positive undertaking as shown in Figure 3. The final-loss is the price of the loss-function at the end of education, at the same time as the minimal loss is the lowest cost of the loss-function accomplished at some point of-schooling. For all three fashions, the final loss is notably low, indicating that they've learned to perform the mission nicely. However, the BiLSTM version has the lowest final loss of 0.0008075 as shown in Figure 3(a), accompanied via the LSTM version with a very last loss of 0.0008225 as indicated in Figure 3(b), and the GRU model with a very last-lack of 0.0008097 as represented in Figure 3(c).



(c)

Figure 3. Performance metrics: training loss of; (a) BiLSTM, (b) LSTM, and (c) GRU

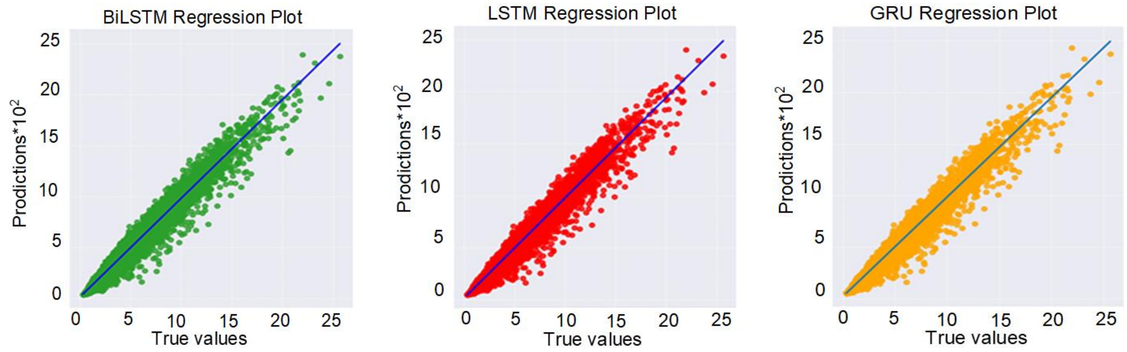
The minimal loss, alternatively, is the bottom cost of the loss-characteristic accomplished during education. The outcomes show that the BiLSTM model completed the lowest minimal loss of 0.001167, followed closely through the GRU version with a minimum lack of 0.001192 and the LSTM model with a minimum loss of 0.001232 as shown in Table 3.

Table 3. The final loss and min loss for 3 models

Model	Final loss	Min loss
GRU	0.0008097	0.001192
LSTM	0.0008225	0.001232
BILSTM	0.0008075	0.001167

Overall, the outcomes endorse that the BiLSTM model outperformed the opposite models in phrases of each very last loss and minimum loss, indicating that it learned the assignment better than the opposite fashions. In this case, the regression plots show the relationship between the true values of the target variable and the predicted values of the target variable by each of the three models: GRU, LSTM, and BiLSTM as shown in Figure 4. The closer the predicted values are to the true values, the more closely the points on the regression line will align with the diagonal line, which represents perfect predictions. Looking at the evaluation metrics, the BiLSTM model has the lowest MAE, RMSE, and MAPE values. Additionally, it has the highest R2 value among the three models, indicating that it explains the variance in the data better than the other two models. Therefore, based on these evaluation metrics, we can finally conclude with all this and everything we obtained in this result that the BiLSTM model is the best regression model among the three models as presented in Figure 4(a).

The results of the analysis show that the BiLSTM model consistently outperformed the GRU and LSTM models in terms of both ultimate loss and minimum loss, it obtained the ultimate loss and minimum loss values, respectively work well in learning the business as observed in Figures 4(b) and (c). Furthermore, the regression plots show that the values predicted by the BiLSTM model agree well with the true values, indicating accuracy. Analytical metrics such as RMSE, MAE, MAPE, R2 further support the superiority of the BiLSTM model, as it obtained the lowest error value and the highest R2 value in conclusion, the BiLSTM model appears as a regression the best example of the three, showing its effective efforts in the assigned task.



(a) (b) (c)

Figure 4. Regression plots for the three model; (a) BiLSTM regression plot, (b) LSTM regression plot, and (c) GRU regression plot

4. CONCLUSION

In conclusion, this study demonstrates that GRU, BiLSTM, and LSTM models can be effectively utilized for intelligent load traffic prediction in 4G LTE cellular networks. Notably, the BiLSTM model outperformed both the LSTM and GRU models across all evaluation metrics, including R2, RMSE, MAE, and MAPE. This enhancement in predictive accuracy suggests that the application of advanced AI techniques is crucial for improving network QoS and optimizing resource allocation. Moreover, the insights derived from this research highlight the potential for predicting traffic patterns in upcoming generations of cellular networks, thereby playing a vital role in the ongoing advancement of cellular technologies. Future research avenues may include the exploration of additional AI methodologies and the examination of real-time data impacts on model accuracy. Collectively, these contributions lay a strong foundation for further investigations into intelligent load traffic prediction and the broader application of AI techniques in network management.

ACKNOWLEDGMENTS

Reviewer's valuable comments are greatly appreciated.

FUNDING INFORMATION

Authors state no funding involved

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Hassnaa Shindou	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
Yassine El Hasnaoui		✓	✓	✓		✓		✓	✓	✓	✓			✓
Srifi Mohamed Nabil	✓			✓		✓		✓		✓		✓	✓	

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

No potential conflict of interest was reported by the authors.

DATA AVAILABILITY

Data will be made available on request.

REFERENCES

[1] H. Zou, Y. Wu, H. Zhang, and Y. Zhan, "Short-term Traffic Flow Prediction Based on PCC-BiLSTM," in *Proceedings - 2020 International Conference on Computer Engineering and Application, ICCEA 2020*, IEEE, Mar. 2020, pp. 489–493, doi: 10.1109/ICCEA50009.2020.00110.

[2] N. Li, L. Hu, Z. L. Deng, T. Su, and J. W. Liu, "Research on GRU Neural Network Satellite Traffic Prediction Based on Transfer Learning," *Wireless Personal Communications*, vol. 118, no. 1, pp. 815–827, May 2021, doi: 10.1007/s11277-020-08045-z.

[3] T. H. H. Aldhyani, M. Alrasheedi, A. A. Alqarni, M. Y. Alzahrani, and A. M. Bamhdi, "Intelligent Hybrid Model to Enhance Time Series Models for Predicting Network Traffic," *IEEE Access*, vol. 8, pp. 130431–130451, 2020, doi: 10.1109/ACCESS.2020.3009169.

[4] H. Mehri, H. Chen, and H. Mehrpouyan, "Cellular Traffic Prediction Using Online Prediction Algorithms," *arXiv*, 2024, doi: 10.48550/arXiv.2405.05239.

[5] K. Park, S. Sung, H. Kim, and J. il Jung, "Technology trends and challenges in SDN and service assurance for end-to-end network slicing," *Computer Networks*, vol. 234, pp. 1–33, Oct. 2023, doi: 10.1016/j.comnet.2023.109908.

[6] S. Zafar, S. Jangsher, O. Bouachir, M. Aloqaily, and J. B. Othman, "QoS enhancement with deep learning-based interference prediction in mobile IoT," *Computer Communications*, vol. 148, pp. 86–97, Dec. 2019, doi: 10.1016/j.comcom.2019.09.010.

[7] Y. El Hasnaoui and T. Mazri, "Comparative study of different dielectric substrates on microstrip patch antenna for new generation (5G)," *Advances in Materials and Processing Technologies*, vol. 8, no. 2, pp. 1400–1407, Apr. 2022, doi: 10.1080/2374068X.2020.1860496.

[8] Y. El Hasnaoui and T. Mazri, "Design of higher gain 1×4 cylindrical dielectric resonator antenna for mm-wave base stations," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 5, pp. 3218–3225, Oct. 2024, doi: 10.11591/eei.v13i5.7966.

[9] V. Kurri, V. Raja, and P. Prakasam, "Cellular traffic prediction on blockchain-based mobile networks using LSTM model in 4G LTE network," *Peer-to-Peer Networking and Applications*, vol. 14, no. 3, pp. 1088–1105, May 2021, doi: 10.1007/s12083-021-01085-7.

[10] F. W. Alsaade and M. H. Al-Adhaileh, "Cellular Traffic Prediction Based on an Intelligent Model," *Mobile Information Systems*, pp. 1–15, Jul. 2021, doi: 10.1155/2021/6050627.

[11] E. Egrioglu and E. Bas, "A new deep neural network for forecasting: Deep dendritic artificial neural network," *Artificial Intelligence Review*, vol. 57, no. 7, pp. 1–25, Jun. 2024, doi: 10.1007/s10462-024-10790-7.

[12] S. T. Nabi *et al.*, "Deep Learning Based Fusion Model for Multivariate LTE Traffic Forecasting and Optimized Radio Parameter Estimation," *IEEE Access*, vol. 11, pp. 14533–14549, 2023, doi: 10.1109/ACCESS.2023.3242861.

[13] M. Hassan and A. Arabiat, "An evaluation of multiple classifiers for traffic congestion prediction in Jordan," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 36, no. 1, pp. 461–468, Oct. 2024, doi: 10.11591/ijeecs.v36.i1.pp461-468.

[14] K. Koutlia, B. Bojovic, S. Lagén, X. Zhang, P. Wang, and J. Liu, "System analysis of QoS schedulers for XR traffic in 5G NR," *Simulation Modelling Practice and Theory*, vol. 125, May 2023, doi: 10.1016/j.simpat.2023.102745.

[15] M. P. P. Flores, J. F. Solis, G. C. Valdez, J. J. G. Barbosa, J. P. Ortega, and J. D. T. Villanueva, "Hurst Exponent with ARIMA and Simple Exponential Smoothing for Measuring Persistency of M3- Competition Series," *IEEE Latin America Transactions*, vol. 17, no. 5, pp. 815–822, May 2019, doi: 10.1109/TLA.2019.8891950.

[16] J. Su, H. Cai, Z. Sheng, A. X. Liu, and A. Baz, "Traffic prediction for 5G: A deep learning approach based on lightweight hybrid attention networks," *Digital Signal Processing: A Review Journal*, vol. 146, Mar. 2024, doi: 10.1016/j.dsp.2023.104359.

[17] T. H. H. Aldhyani, M. R. Joshi, S. A. Almaaytah, A. A. Alqarni, and N. Alsharif, "Using Sequence Mining to Predict Complex Systems: A Case Study in Influenza Epidemics," *Complexity*, no. 1, pp. 1–16, Jan. 2021, doi: 10.1155/2021/9929013.

[18] A. Q. Md *et al.*, "Novel optimization approach for stock price forecasting using multi-layered sequential LSTM," *Applied Soft Computing*, vol. 134, Feb. 2023, doi: 10.1016/j.asoc.2022.109830.

[19] A. Navarro-Espinoza *et al.*, "Traffic Flow Prediction for Smart Traffic Lights Using Machine Learning Algorithms," *Technologies*, vol. 10, no. 1, pp. 1–11, Jan. 2022, doi: 10.3390/technologies10010005.

[20] Y. Su and X. Jiang, "Prediction of tide level based on variable weight combination of LightGBM and CNN-BiGRU model," *Scientific Reports*, vol. 13, no. 1, pp. 1–13, Jan. 2023, doi: 10.1038/s41598-022-26213-y.

[21] S. P. Sone, J. J. Lehtomäki, and Z. Khan, "Wireless Traffic Usage Forecasting Using Real Enterprise Network Data: Analysis and Methods," in *IEEE Open Journal of the Communications Society*, vol. 1, pp. 777-797, 2020, doi: 10.1109/OJCOMS.2020.3000059.

[22] S. Arshi, L. Zhang, and R. Strachan, "Weather Based Photovoltaic Energy Generation Prediction Using LSTM Networks," *International Joint Conference on Neural Networks (IJCNN). IEEE*, 2019, pp. 1–8, doi: 10.1109/IJCNN.2019.8852206.

[23] Z. Wu, "The comparison of forecasting analysis based on the ARIMA-LSTM hybrid models," in *Proceedings - 2021 International Conference on E-Commerce and E-Management, ICECEM 2021*, IEEE, Sep. 2021, pp. 185–188, doi: 10.1109/ICECEM54757.2021.00044.

[24] A. H. Bukhari, M. A. Z. Raja, M. Sulaiman, S. Islam, M. Shoaib, and P. Kumam, "Fractional neuro-sequential ARFIMA-LSTM for financial market forecasting," *IEEE Access*, vol. 8, pp. 71326–71338, 2020, doi: 10.1109/ACCESS.2020.2985763.

[25] C. Zhang, H. Zhang, D. Yuan, and M. Zhang, "Citywide Cellular Traffic Prediction Based on Densely Connected Convolutional Neural Networks," *IEEE Communications Letters*, vol. 22, no. 8, pp. 1656–1659, Aug. 2018, doi: 10.1109/LCOMM.2018.2841832.

[26] Y. E. Hasnaoui and T. Mazri, "Study, design and simulation of an array antenna for base station 5G," *In: International Conference on Intelligent Systems and Computer Vision (ISCV)*, Feb. 2020, pp. 1-5, doi: 10.1109/ISCV49265.2020.9204261.

[27] P. Rebari and B. R. Killi, "Deep Learning Based Traffic Prediction for Resource Allocation in Multi-Tenant Virtualized 5G Networks," in *IEEE Region 10 Annual International Conference, Proceedings/TENCON*, IEEE, Oct. 2023, pp. 97–102, doi: 10.1109/TENCON58879.2023.10322446.

BIOGRAPHIES OF AUTHORS

Hassnaa Shindou received a Master's degree in embedded systems and telecommunication systems from Ibn Tofail University, Morocco, in 2020. She is a Ph.D. student of the Advanced Systems Engineering Laboratory (ASE) at ENSA Kenitra. Her current research interests include telecommunications systems, wireless communication networks, and signal processing and mobile network prediction. Degree in software engineering in 2024 from ALX. She can be contacted at email: hassnaa.shindou@uit.ac.ma.

Yassine El Hasnaoui received a Master's degree in embedded systems and telecommunication systems from Ibn Tofail University, Morocco, in 2019. He did his Ph.D. in 2024 within Electronics and Telecommunications of the Advanced Systems Engineering Laboratory (ASE) at ENSA Kenitra. His current research interests include the design and optimization of antennas for 5G mobile networks, antennas and modeling of planar microwave circuits, dielectric resonator antennas, and other wireless communication systems. He can be contacted at email: yassine.elhasnaoui@uit.ac.ma.

Srifi Mohamed Nabil was born in Sidi Redouane Ouezzane, Morocco, in January 1978. He received the Licence de Physique degree in electronics from Ibn Tofail University, Kenitra, Morocco, in 1999, and the Deep Higher Studies Diploma DESA degree in telecommunications systems and the Ph.D. degree in electrical engineering from Abdelmalek Essaadi University, Tetuan, Morocco, in 2004 and 2009, respectively. He is currently an Assistant Professor of Electrical Engineering at Ibn Tofail University, Morocco. His research interests include biological efects of radiofrequency and microwave, bio-electromagnetics, biomedical engineering, and antenna design. He holds two patents on antennas for ultra-wide band applications. He can be contacted at email: srifimn@uit.ac.ma.