IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received May 30, 2020, accepted July 5, 2020, date of publication July 14, 2020, date of current version July 27, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3009169

Intelligent Hybrid Model to Enhance Time Series Models for Predicting Network Traffic

THEYAZN H. H ALDHYANI[1], MELFI ALRASHEEDI[2], AHMED ABDULLAH ALQARNI[3], MOHAMMED Y. ALZAHRANI[3], AND ALWI M. BAMHDI[4]

[1]Community College of Abqaiq, King Faisal University, Al-Hasa 31982, Saudi Arabia
[2]Department of Quantitative Methods, School of Business, King Faisal University, Al-Hasa 31982, Saudi Arabia
[3]Department of Computer Sciences and Information Technology, Albaha University, Al baha 65431, Saudi Arabia
[4]College of Computing, Umm Al-Qura University, Makkah 24231, Saudi Arabia

Corresponding author: Theyazn H. H Aldhyani (taldhyani@kfu.edu.sa)

This work was supported by the Deanship of Scientific Research at King Faisal University through Nasher Track under Grant 186395.

ABSTRACT Network traffic analysis and predictions have become vital for monitoring networks. Network prediction is the process of capturing network traffic and examining it deeply to decide what is the occurrence in the network. The accuracy of analysis and estimation of network traffic are increasingly becoming significant in achieving guaranteed Quality of Service (QoS) in the network. The main aim of the presented research is to propose a new methodology to improve network traffic prediction by using sequence mining. The significance of this important topic lies in the urge to contribute to solving the research problem in network traffic prediction intelligently. We propose an integrated model that combines clustering with existing series models to enhance prediction the network traffic. Clustering granules are obtained using fuzzy c-means to analyze the network data for improving the existing time series. The novelty of the proposed research has used the clustering approach to handle the ambiguity from the entire network data for enhancing the existing time series models. Furthermore, we have suggested using the weighted exponential smoothing model as preprocessing stages for increasing the reliability of the proposed model. In this research paper, machine intelligence proposed to predict network traffic. The machine intelligence is working as pre-processing for enhancing the existing time series models. The machine intelligence combines non-crisp Fuzzy-C-Means (FCM) clustering and the weight exponential method for improving deep learning Long Short-Time Memory(LSTM)and Adaptive Neuro-Fuzzy Inference System (ANFIS)time series models. The ANFIS and LSMT time series models are applied to predict network traffic. Two real network traffic traces were conducted to test the proposed time series models. The empirical results of proposed to enhanced LSTM 97.95% and enhanced ANFIS model is R = 96.78% for cellular traffic data, with respect to the correlation indicator. It is observed that the proposed model outperforms alternative time series models. A comparative prediction results between the proposed model and existing time series models are presented. The comparisons indicate that the presented model outperforms the opponent models; the proposed method optimises the deep learning LSTM and ANFIS time series models. The proposed methodology offers more effective approach to the prediction of network traffic.

INDEX TERMS Machine intelligence, soft computing, machine learning, network traffic, deep learning algorithm.

I. INTRODUCTION

Network traffic management is defined as an aspect of network traffic analysis and prediction. Internet traffic management is used to handle the traffic situations in networks, avoiding congestion, improving information security and making good use of available network resources. With the propagation of smart phones and using data plans by the majority, data traffic is experiencing exponential growth. To manage the harnessing of this explosive growth, accurate network traffic forecasting is required for planning the capacity of networks. In the absence of a fast and accurate network traffic-forecasting model, network operators will be at risk. Network management and appropriate

The associate editor coordinating the review of this manuscript and approving it for publication was Mouloud Denai.

modelling are necessary for effective network traffic management.

With the developing prevalence of advanced mobile phones and the fast improvement of the Internet, the conventional system administration framework cannot adjust intelligently and sufficiently. Moreover, if we can use historical data to forecast the patterns of network traffic accurately, better planning of network is more likely to be made, and limited resources can be allocated and scheduled reasonably. Modelling and forecasting of network traffic also play important roles in achieving the most favourable resource allocation by convenient bandwidth provisioning and simultaneously preserving the highest network utilisation. Thus, it is crucial to have a vigorous forecasting model for planning and designing the capacity of the network. The dynamic nature of network traffic influences the need for a way to dynamically allocate bandwidth and avoid congestion. Measuring network traffic behaviours can only be achieved if we have an accurate model. Consequently, accurate network traffic modelling and prediction is required in order to accomplish a better Quality of Service (QoS) and for best future network traffic engineering. Furthermore, the linear as well as non-linear time series models have been widely utilised for modelling of network traffic by many developers and researchers.

Network traffic prediction models can assist network engineers in determining appropriate traffic engineering tools that can even deal with any unexpected future conditions automatically. Network traffic prediction algorithms can absolutely play a vital role in network planning and bandwidth provisioning. Network traffic planning has become a very important task in the research community. Due to the capacity of the telecommunication network, it has become very difficult for an administrator to manage the network since users are connecting to it. Further, monitoring network between source and destination is a very important task, and this needs accurate modelling of incoming traffic as well as prediction of future traffic. Network traffic analysis has become ever more vital and important for monitoring network traffic. Network analysis is a process of capturing network traffic and examining it deeply to decide what is the occurrence in the network. Network analysis is identified by numerous other names: network analysis, protocol analysis, packet analysis and others [1]. Network traffic analysis is a set of methods that are consecutively utilised to understand the nature of traffic on a per-packet or per-level basis. Furthermore, network traffic analysis is used to analyse all traffic data, which includes the time and duration of the communication, the complicated shape of the communication streams, the identities of the groups communicating, and their locations. Thus, modelling network traffic has become an essential part of helping to design networks and of bandwidth wastage control. The Poisson model is the original model that is implemented in the telephone network for the modelling and prediction arrival process [2]. Nevertheless, with the emergence of modern telecommunication, network traffic has developed massively and is becoming increasingly complex and burst than earlier voice traffic. Network management and appropriate modelling are necessary for effective network traffic management.

A number of researchers and developers have studied these issues, and intelligence algorithms are employed for modelling and predicting network traffic.

These intelligence algorithms are the genetic algorithm [2], [3], the Artificial Neural Network [4], fuzzy logic [5], and so on. They combine neural network with a fuzzy logic-proposed robust model able to enhance the prediction of network traffic [6]. The combination has given the highest performance compared to the individual. Proposed feedback on this method is that the Recurrent Convolution Neural Network be used to predict the traffic [7]. Also, the DNN deep learning model can be used to predict traffic flow. The results have shown that deep learning reduces prediction errors [8]. The significance of this important topic, and our urge to contribute in solving the research problem in network traffic prediction intelligently, are the main motive of this research. Consequently, accurate network traffic modelling and prediction are a requisites to accomplishing a better Quality of Service (QoS) and for best future network traffic engineering.

The contributions of this research are: modelling and forecasting of network traffic also play an important role in achieving the most favorable resource allocation by provisioning a convenient bandwidth and simultaneously preserving the highest network utilization. Clustering granules are obtained using fuzzy c-means to analyze the network data for improving the existing time series. The novelty of the proposed research has used the clustering approach to handle the ambiguity from the entire network data for enhancing the existing time series models. Furthermore, we have suggested using a weighted exponential smoothing model as preprocessing stages for increasing the reliability of the proposed model. Finally, the proposed model has achieved the best results compared with the existing time series models.

Whether the research work is rich and depth for determine the ambiguous objects that obstruct the performance of time series models. Using machine intelligence has made research work is rich and depth.

- We proposed a hybrid model to predict network traffic.
- We used advance time series prediction models for improving network congestion.
- We have used different types of network data for testing the proposed model.
- The proposed model enhances the alternative time series models
- We compared the results of the proposed model against the results obtained from the alternative model.

II. BACKGROUND OF THE STUDY

The state-of-the-art network traffic research models are summarised, it is observed that the rear research gaps which motivate the proposed research work. Understanding network traffic for predicting future demand is one of the critical requirements for improving network resource efficiency due to complex in-network data from numbers of network applications that are behind the traffic [3]. Numbers of time series models like statistical models and machine learning models have been proposed to deal with network traffic and for predicting traffic: statistical learning [4], [5], machine learning [6]–[9], and hybrid schemes [10]. A comprehensive review of network traffic prediction schemes, and deep learning algorithms is used to improve the efficiency of network traffic throughout predicting future traffic. The convolution and recurrent neural networks are used for prediction network demand [11], [12]. In [13], a deep learning algorithm like convolution and recurrent neural networks to enhance are applied to predict performance. In [14], [9] the LSTM is applied to predict network traffic. In network traffic prediction, the researchers have applied different appropriate models for enhancing network performance. In [15], the ON-OFF model is used and the ARIMA model applied, [16] presents the FARIMA model, [17]considers the mobility model, [18] explores the network traffic model, [19] uses the stable model; [20], [21] these present models were implemented to explore the network traffic characteristics, such as performance, planning, trend and seasonal traffic further, [22] and their self-similarity [23], [24]. The modern signal processing algorithms are used to predict the characteristics of network traffic such as in [25]. [26] is introduced the principal components analysis method. In [26], [27] the Kalman filtering method is applied, and [28], [29], [25], [30] presented a compressive sensing method to capture the evolution of traffic. The modelling network traffic is very important in large scale networks for planning and it increases the performance of the network. In [31], [32], [33] the ARMA model to predict network traffic is proposed. [34], [35] present the ARIMA model to analyse and predict future traffic in the network. In [36], [37] nonlinear models like deep learning and neural network are proposed to predict network traffic. There are numerous significant time series prediction models in the literature, as we will show. The most popular and commonly used time series models are stochastic time series models, such as the Single Moving Average, Holt-Winters, Exponential Smoothing [38] and AutoRegressive Moving Average (ARMA) models. The stochastic time series models are considered as linear time series. The AutoRegressive Moving Average model has branches of other models, such as the AutoRegressive [39] Moving Average, AutoRegressive Moving Average and Seasonal AutoRegressive Moving Average models. The Box and Jenkins method has been proposed for seasonal time series forecasting such as SARIMA model [40].

Wu *et al.* [7] presented the Fusion Deep Learning (FDL) model for predicting level traffic speed. It is noted the proposed model achieved better than the benchmark models with respect to the accuracy and stability metrics. Li *et al.* [60] proposed Dynamic Radial Basis Function (DRBF) neural network to predict outbound passenger volume. The proposed model was use to improve the passenger flow control to identify the Possible stations that significantly impact the outbound volumes of the target stations. Gu *et al.* [61] used deep feature leaning model to predict short-term traffic. The proposed model is used to forecast traffic flow for next day. Furthermore, presented multi-objective particle swarm optimization algorithm to optimize the parameters of deep learning model. Gu *et al.* [62] proposed DNN-BTF model to predict the characteristics of traffic flow. Li *et al.* [63] proposed Bayesian combination model with deep learning (IBCM-DL) to predict traffic flow. The BCM has been used to established the proposed model, Three sub-predictors namely neural network, autoregressive integrated moving average, and RBFNN are appropriated with IBCM framework for improving the proposed model. It is noted that the IBCM-DL model outperforms compared with state-of-the-art models. This research contributes to predicting network traffic for improving network planning, network security, and network management. The new proposed model is suggested to enhance the alternative models. This model can assist in predicting loading packets and burst arrivals of packets in network. We have developed machine intelligence that can forecast traffic in network. Table 1 summarize recent and advancement research papers of network traffic classification and prediction.

III. MATERIALS AND METHODS

In this section, the materials and methods of the proposed model are presented.

Figure 1 shows the formwork of the proposed model to optimise the time series models for predicting network traffic. This new methodology has optimised deep learning LSTM and ANFIS time series models. Real network data were collected from different network backbones for examining the methodology of the proposed model. The fuzzy c-means clustering algorithm has been applied to cluster the network data for identifying the similar characters of objects that are used to pick up similar objects and maintain on specific cluster numbers. The similar objects are clustered into same group, five clusters numbers are considered due to all objects belonging to five cluster numbers. The five clusters numbers $C_1 \rightarrow C_5$ is are initialled as input for the weighted exponential smoothing method. The WES method is applied to predict each cluster's number separately. The weighted exponential smoothing method obtained five predictors $P_1 \rightarrow .P_5$. The predictors $P_1 \rightarrow P_5$ are combined to obtain P_n. The P_n is considered as input for the LSTM and ANFIS time series models. This pre-processing step has been considered to improve the LSTM and ANFIS models to predict network traffic. It is noted that the proposed model has reduced prediction errors and the obtained results were more satisfactory.

Finally, evaluation indicators are employed to examine the proposed methodology to optimise the advance machine learning algorithm, namely LSTM and ANFI, for prediction the network traffic. The algorithm of the proposed model is presented in algorithm 1.1.

TABLE 1. Summaries of network traffic study.

Authors	Years	Data sets	Purpose of the research	Models	Application domain
Amin Azari et al. [41]	2019	Network 5G data generated by using software	Prediction and classification	LSTM and ARIMA	Cellular Traffic
Xu Wang et al. [42]	2019	Major cellular carrier in a big city of China	Prediction	Spatio-Temporal Analysis	Cellular Traffic in Metropolis
Chaoyun Zhang et al. [43]	2018	Mobile traffic from urban and rural areas	Prediction	STN	Long-Term Mobile Traffic
Vincenzo Sciancalepor et al. [44]	2017	Building 5G network	Forecasting	Slicing building block	Mobile Traffic Forecasting
WangyangWei et al. [45]	2019	Real network traffic dataset of PeMS	Prediction	AutoEncoder and LSTM	Long-term Traffic Flow Prediction
Bing Liu et al. [46]	2019	Real Abilene backbone network	Prediction	Linear regression model	Prediction network Traffic Flow Power in WAN
Shulin Cao et al. [47]	2019	Simulation data	Prediction	LSTM	Prediction Traffic Flow in Cellular Networks
MuhammadFaisal Iqbal et al. [48]	2018	Bell core Research trace and university of Aucklandand CAIDA	Prediction	AR, ARMA, ANN and Wavelet	Prediction resource allocating power in network
Chih-Wei Huang et al. [49]	2017	Telecom Italia	Prediction	Deep learning CNN and RNN	Mobile Traffic Forecasting
Hoang Duy Trinh et al. [50]	2018	Physical Downlink Control Channel(PDCCH)	Prediction	LSTM	Mobile Traffic Prediction
Roughan et al. [51]	2004	Waikato trace, streaming data	Classification	K-NN	Classification network at Packet-level and flow-level
Auld et al. [52]	2004	Collected the data from own network	Classification	BN	Packet-level and flow-level
Este et al. [53]	2007	LBNL CAIDA proprietary: campus network	Classification	SVM	Packet payload size
Amaral et al. [54]	2013	Collected the data from own campus Open Flow protocol	Classification	Supervised RF, SGBoost, XGBoost	Packet size and packet time port, flow duration, packet count byte count
Cortez et al. [55]	2016	ISP backbone	Prediction	NEE	Prediction Traffic volume
Bermolen et al. [56]	2006	Internet traffic collected at the POP of an ISP network	Prediction	SVR	Prediction network load
Zhu et al. [57]	2009	Traffic measurements	Prediction	MLP-NN with PSO-ABC	Predict traffic volume
Li et al. [58]	2013	Network of Baidu	Prediction	MLP-NN	Predict traffic volume

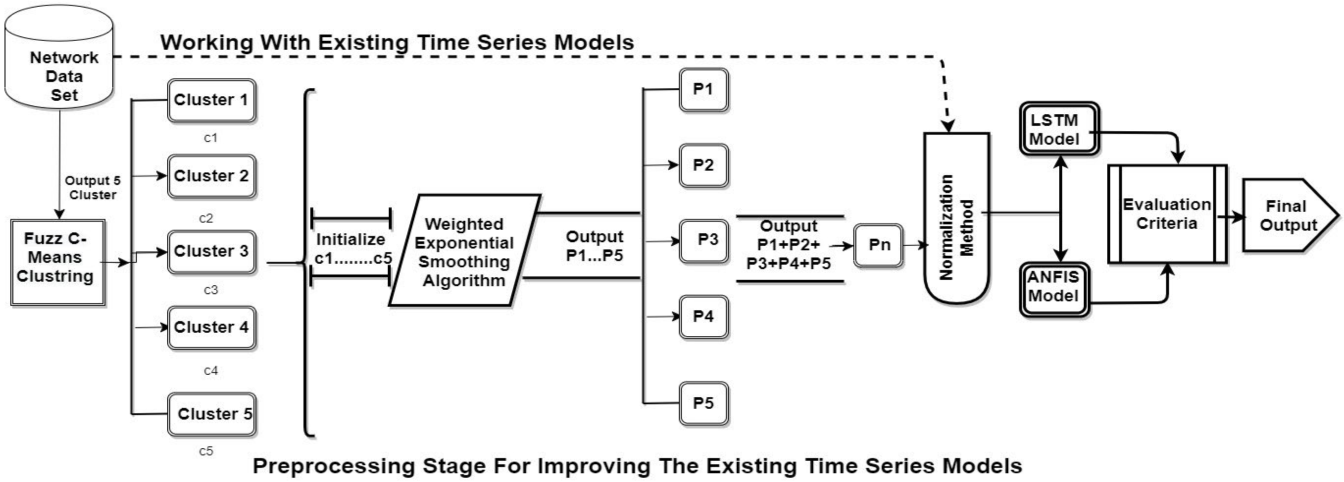


FIGURE 1. Framework of the proposed model.

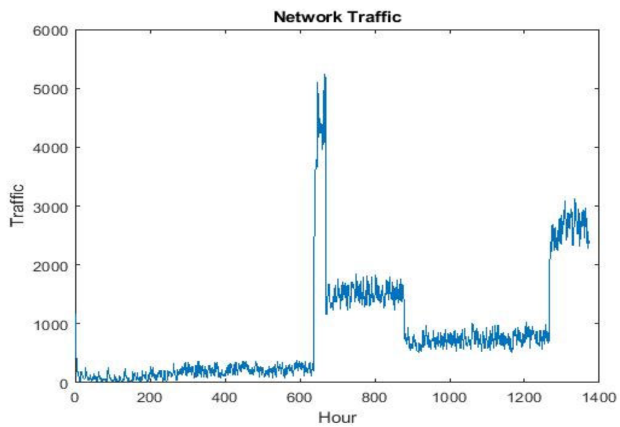


FIGURE 2. Network structure of a cellular network.

Algorithm 1.1 Algorithm of the Proposed Model

Input: Network traffic X_i from different real networks
Output: forecasting the future traffic Y_{i+1}

1. Clustering input data X_i into five clusters C_5 by using Fuzzy C-Means
2. The five clusters are considered as input $C_1 \ldots C_5$
3. Weighed exponential smoothing is applied to individual clusters for obtained P_i
4. Length ($C_1 \ldots C_5$)
5. $fori = C_1 \rightarrow C_5$
6. $P_i \quad =$ alpha $*C_{1\rightarrow 5}$ (i-1) + (1-alpha)$*P_i$ (i-1);
7. Obtained five predicts P_1,P_2P_3, P_4, P_5
8. Combines $P_1 + P_2 + P_3 + P_4 + \quad P_5$ obtained P_n
9. Normalised log(P_n)
10. Apply time series models namely LSTM and ANFIS
11. End for
12. Return Y_{i+1}

A. DATASETS

The real network traffic traces are conducted to test the performance of the proposed model.

1) 4G CELL TRAFFIC FROM KAGGLE

The q-data collected from Kaggle data set contains loading packets of 4G cells. 4G cell traffic is known as the traffic of users of a mobile data service; the mobile device will be served by a nearby 4G cell. The data contains one week of traffic; Cell 039872 is serving 50 subscribers, and each subscriber in 1 hour x uses an average of 10Mb => Traffic of cell 039872 [57]. In this research, one day (10-16-2016) of traffic was considered to test the proposed model. Figure 2 shows the load packets for one day. Figure 3 shows the structure of the cellular network.

2) MAWI (MEASUREMENT AND ANALYSIS ON THE WIDE INTERNET)

This trace is collected from a backbone of WIDE internet with a connection speed of 150 Mbps. The MAWI (Measurement and Analysis on the WIDE Internet) repository contains numbers of network traffic data [58]. The WIDE is the backbone of a Japanese academic network. We have considered the 2015 traffic trace. Figure 4 displays the load packets traffic in 2015 after being normalized by using a log function.

B. FUZZY C-MEANS (FCM) METHOD

Fuzzy c-means clustering is a non-crisp clustering algorithm which uses to all object value to be a member to one or more with different value is considered between [0,1]. The non-crisp FCM gives a varying membership value to the objects in the same cluster. The equation [1] is represented as FCM. The figure displays how FCM algorithm clusters the objects.

$$\sum_{i=1}^{n}\sum_{j=1}^{k}\mu_{ij}^{m}\left(\vec{x},\vec{c}\right)1 < m < \infty \tag{1}$$

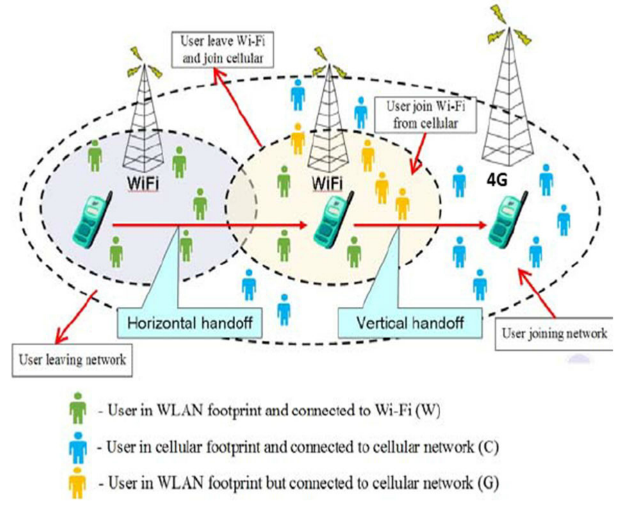


FIGURE 3. **Load network traffic for one day.**

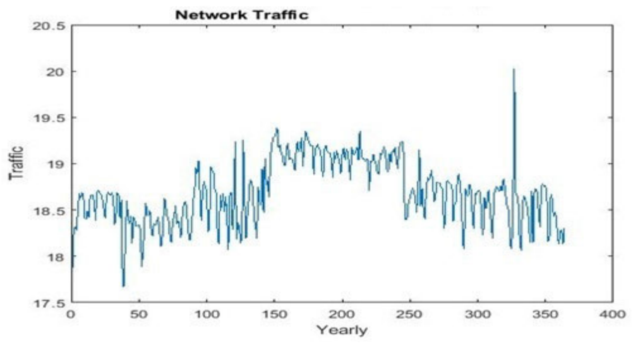


FIGURE 4. **Load network traffic for one year.**

where n is the number of the load packets in network traffic, m is the real number great than 1performed by μ_{ij} membership function, $\vec{c}$ is centroid $\vec{x}$ is vector numbers j is cluster numbers.

Subject to update the membership function in

$$U_{ij} = \frac{1}{\sum_{n=1}^{k} \left(\frac{d(\vec{x}_i - \vec{c}_i)}{\vec{x}_i - \vec{c}_i)}\right)^{\frac{2}{m-1}}} \quad (2)$$

Subject to update the appropriate centroid for the objects

$$\vec{c}_i = \frac{\sum_{i=1}^{n} \mu_{ijX_i}^{m}}{\sum_{i=1}^{n} \mu_{ij}^{m}} \quad (3)$$

Algorithm FCM clustering is presented in algorithm 2.2.

C. WEIGHT EXPONENTIAL SMOOTHING (WES) METHOD

Exponential smoothing models are some of the most popular prediction models and some of the most important prediction approaches widely used in industry and commerce. The five $C_1 \rightarrow C_5$ cluster numbers obtained from FCM clustering are initiated as input. The WES method is applied to five

Algorithm 2.2 FCM Algorithm

1. Inpu x_i
2. Output c_1, c_2, c_3, c_4, c_5
3. Initialise the μ_{ij}^{m}
4. $for\ i = 1 to\ n$
5. $for\ k = 1 to\ j$
6. Repeat j=1,2,3
7. Update the membership function using U_{ij} in eq (2)
8. Update the centroi C_i d by using Eq [3]
9. Until
10. Max $(|U_{ij}^{t+1} - U_{ij}^{t}|)\delta$
11. where δusetoterminatebetween0 and 1
12. End
13. End

cluster inputs individually for obtaining five predictors that can improve the existing time series models. Algorithm WES clustering is presented in algorithm 3.3.

$$l_0 = \bar{X} = \frac{\sum_{t=1}^{n} Xy_t}{n}$$
$$P_{T+1} = \alpha y_t + (1-\alpha)P_t \quad (4)$$

where, S_{T+1} remains constant and S_t is smoothing data.

Output $P_1 \rightarrow P_5$

Algorithm 3.3 WES Algorithm

Input five clusters
c_1, c_2, c_3, c_4, c_5
Output five predictors $p_{1,}p_2\ p_3\ p_4\ p_5 = P_n$
Initialise input
data c_1, c_2, c_3, c_4, c_5
Give value of constant parameter α
n length data
$for\ i = 1 to\ n$
Repeat i
Until end P_{T+1}
End

D. NORMALIZATION

Normalisations a pre-processing method use to reformat and manipulate real network data. The normalization is used to enhance the time series model by scaling the data and transformation from one form into another form. The main object of using the normalization method is to scale the data and so prevent the greatest numeric ranges from dominating in the smaller numeric range. The min-max method is applied to scaling network traffic data. This method has transformed data within a range of 0 to 2 scales.

$$z_n = \frac{x - x_{min}}{x_{max} - x_{min}} \left(New_{max_x} - New_{min_x}\right) + New_{min_x} \quad (5)$$

where, New_{max_x} and New_{min_x} is range number between the 0 to 2.

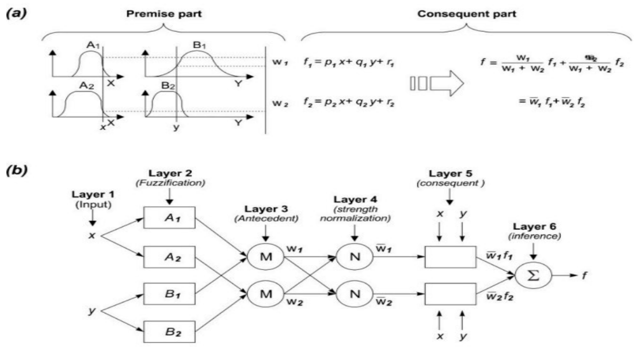


FIGURE 5. Type fuzzy reasoning for ANFIS.

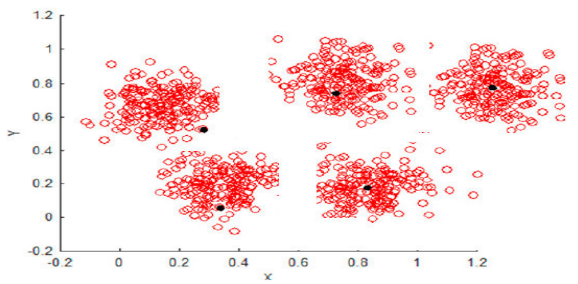


FIGURE 6. Five clusters obtained from FCM.

E. TIME SERIES MODELS

In this section, two advanced existing models are presented to predict network traffic:

1) ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a powerful time series model that combines fuzzy logic and the neural network algorithm [25], [16] . The ANFIS model is used to move the input data to obtain appropriate output; it uses the concept of a non-linear model to filter high dimension data. The ANFIS model has two inference systems, the Sugeno inference system and the Mamdani inference system, which are presented in the literature [27], [28]. The fuzzy rules for these two inference approaches are different in aggregation and defuzzification. Assume that the ANFIS model has two inputs x_1y_1 and one output z and thus the fuzzy rules have two fuzzy sets:

FIGURE 5. Displays type-3 fuzzy reasoning. This corresponding equivalent ANFIS architecture (type-3 ANFIS) is illustrated in figure (b). The function node in the same layer is called a function family. Table 2 describes the ANFIS layers for prediction network traffic. This function is described below:

The ANFIS algorithm has two methods to predict time series data; the grid partition is the approach used to divide space in to grid-Sam as a structure for avoiding overlap ping parts in inputs space. When the grid partition approach is applied in a specific area which has fuzzy rules, the fuzzy rules can be more smoothly analysed. The grid partition is

TABLE 2. Layers of ANFIS model for prediction network traffic.

Layer 1: (input layer):	Assume that the ANFIS model has two **inputs$x_1y_1$and one output z** and thus the fuzzy rules have two fuzzy sets**:** Rule1: if x is $A_1$and y is B_1, then f_1=$p_1x_1 + q_1y + r_1$, (6) Rule2: if x is $A_2$and y is B_2, then f_2= $p_2x_1 + q_2y + r_2$, (7)
Layer2: (Fuzzification layer)	This layer is known as the fuzzification layer. Each node in this layer is square node i which presents by: $O_{1,i}$ =μA_i(x) for $i = 1,2$ (8) $O_{1,i}$=$\mu B_i - 2$(y) for $i = 1,2$ (9) $\mu A_i(x_1) = \frac{1}{1+(\frac{x-c_i}{a_i})^{2b_i}}$ (10) Where x and y are the input parameters to node i, A and B are the linguistic labels associated with this node, $\mu(x)$ and $\mu(y)$ are membership functions. A Gaussian shaped function, ranging from 0 to 1.0, is typically adapted. The a_i, b_i and c_i are the parameters of Bell function.
Layer3: (Antecedent layer)	In the third layer, the input value has become the membership, and each node multiplies input signals to obtain outputs. The firing strength is represented by each node output. $O_{2,i}$==$w_i = \mu A_i(x) * \mu B_i(y)$, $i = 1,2$ (11) where, the signal firing strength for the rules are present by w_i
Layer 4 (Strength normalization layer)	In the third layer, calculate the i^{th}node by using the ratio ofi^{th} value of firing strength by the sum of the rule's firing strength. $O_{3,i}$=$\bar{w}_i$=$\frac{w_i}{w_{1+w_2}}$, $i = 1,2$ (12) The output of this layer can be called normalised firing strengths. Layer 4:in the fourth layer, nodes are adaptive nodes.
Layer5: (Consequent layer)	The output of this layer can be called normalised firing strengths. Layer 4:in the fourth layer, nodes are adaptive nodes. $O_{4,i} = \bar{w}_i.f_i = \bar{w}_i.(p_ix + q_iy + r_i)$ (13) Where $\bar{w}$is the output of layer 3, whilep_i, q_i, r_i are the parameters.These parameters are consequent parameters in this layer.

TABLE 2. ***(Continued.)*** **Layers of ANFIS model for prediction network traffic.**

Layer6: (Inference layer)	In this layer, the single fixed node is presented as a summation that computes the overall output as the summation of all incoming signals. $O_{5,i} = overalloutput = \sum \overline{w}_i f_i = \frac{\sum_i \overline{w}_i f_i}{\sum_i w_i}$ (14)

TABLE 3. **Parameters of ANFIS model.**

Parameter Names	Numbers
Parameter cluster	5
Partition matrix	2
Maximum number of iterations	100
Minimum improvement	1e-5
Maximum number of epochs	100
Error Goat	0
Initial steps size	0.01
Step size decrease-rate	0.9
Steps size-increase	1.1

TABLE 4. **Parameters of LSTM algorithm.**

Parameter Names	Numbers
Num Hidden	250
Max Epochs	**200**
Mini Batch Size	**120**
Max Iterations	**500**
Shallow hidden Layer Size	**[30 50]**

used when input space is very small and when the dimension vector is very small. One of the biggest problems is that the grid partition is accepted by only a small input space. In order to solve this problem for increasing the performance of the ANFIS algorithm, a scatter partition is presented. The scatter partition method has the ability to accept large numbers of input space with different dimension vectors. The scatter partition method divides the dimension vectors into cluster numbers in specific areas of fuzzy rules that help to take large input spaces. The cluster numbers in the scatter partition method have some numbers of fuzzy rules in a specific area in fuzzy. There are a number of methods in scatter partition, such as FCM clustering, subtractive clustering and context-based fuzzy c-means clustering. In this research, we have used FCM clustering and aback propagation algorithm for learning. This hybrid time series model is used to learn for prediction network traffic. Table 3 shows the proposed parameters of the ANFIS model to improve the performance of network traffic.

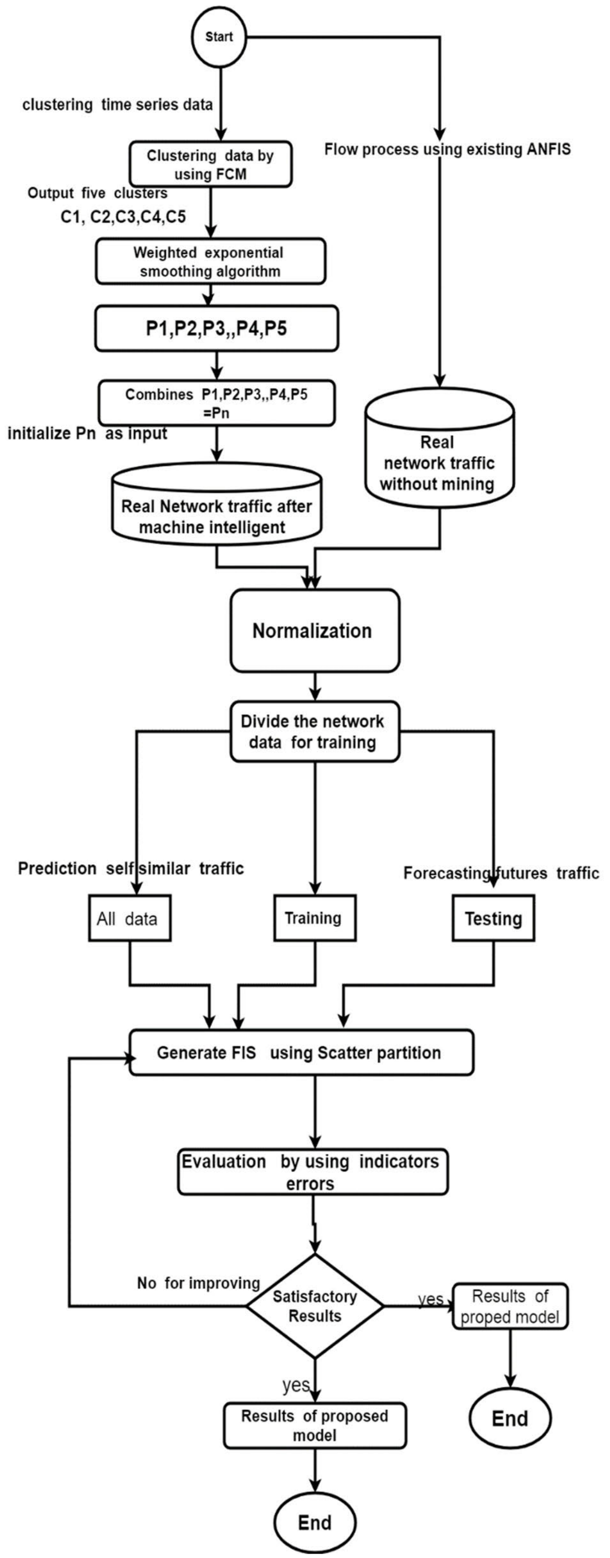


FIGURE 7. **Process steps of the proposed model to enhance the ANFIS model to predict network traffic.**

These parameters were more appropriate for reducing the prediction and for increasing the performance of the proposed model. As we observed, prediction errors of output are minimised by giving input data. When the proposed processing

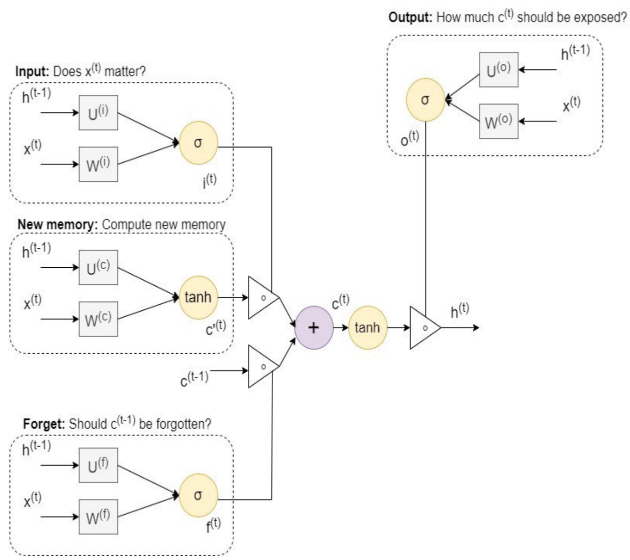


FIGURE 8. **Structure of deep learning LSTM algorithm.**

is applied to mining the input data, the ANFIS obtains a satisfactory output. Figure 7 shows the flow process of the ANFIS model to predict the network.

The process of ANFIS is repeated until the error of the threshold is reached or when the number of repetitions stated by the user is reached. Figure 6 shows the learning process of the ANFIS model. Five clusters are considered to generate the fuzzy rules to predict network traffic. The appropriate processes to create the fuzzy rules are shown in Table 3.

2) RECURRENT NEURAL NETWORK (RNN)

The Recurrent Neural Network(RNN)was designed in the 1980s [59]. The RNN algorithm consists of hidden layers, an input layer and an output layer. The RNN algorithm has a chain like-structure for repeating cells of the RNN algorithm, used to store significant information from previous process steps. The RNN has a feedback loop that permits NN to arrange and accept a sequence of input data, unlike a feedback neural network. Furthermore, the RNN is successfully algorithmic in sequence learning. The Long Short-Time Memory (LSTM) neural network algorithm is an RNN algorithm that uses in series time domain. The LSTM algorithm has memory because the LSTM algorithm uses a block chain like structure that can help the algorithm to learn long indecencies. The states like the cell state and the hidden state, are transferred to the next significant cell. The data flow chain is considered by main cell state. The information in state cell can be added or removed by sigmoid function. from the cell state. A gates of LSTM model has layers or series which has different matrix operations. The first step in creating an LSTM network is to define non-required and excluded data from the cell in that process. Table 4 shows the parameters of LSTM to predict traffic. Figure 8 displays the structure of deep learning LSTM algorithms that are considered to obtain prediction results. Figure 9 displays the flow steps of the proposed model to optimise the LSTM algorithm.

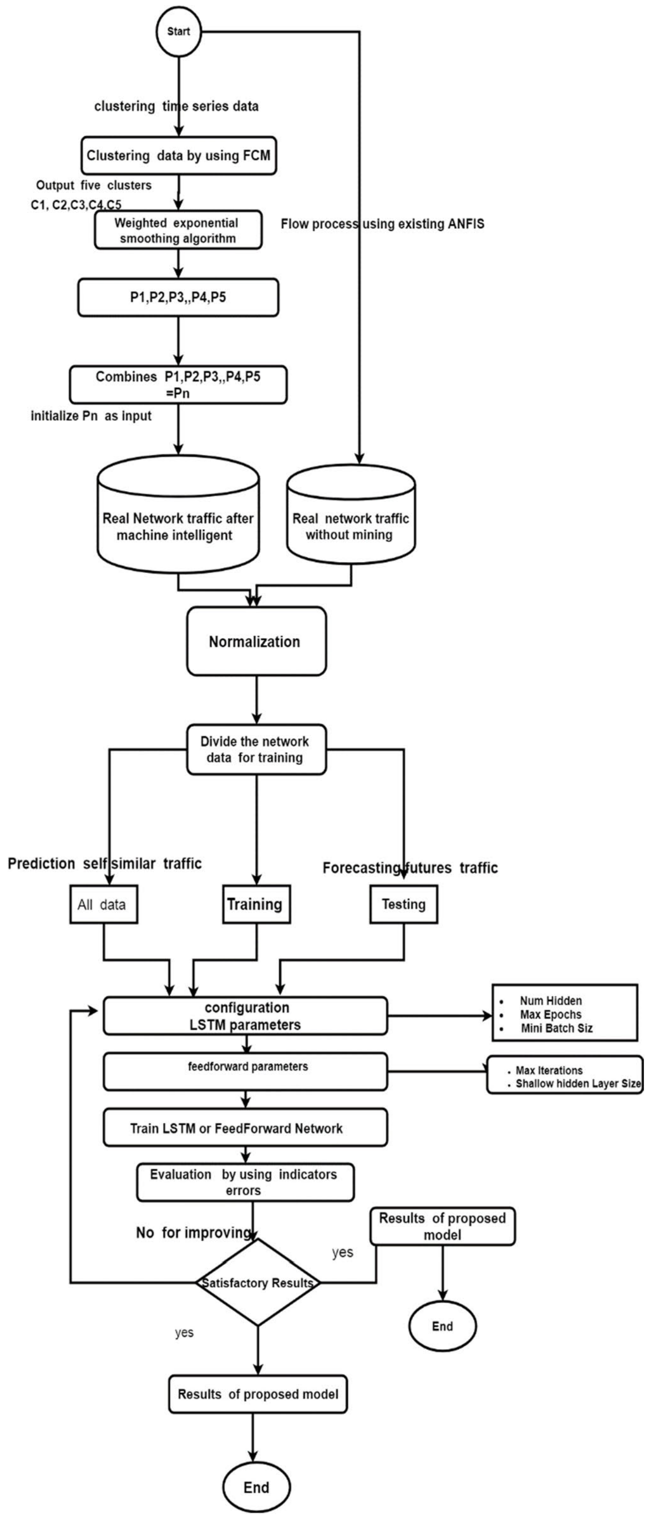


FIGURE 9. **Flow steps of the proposed model to enhance deep learning LSTM model for predicting network traffic.**

$$h_t = \text{sigm}(W_{xt} + Uh_{t-1} + b^{(h)} \tag{15}$$

$$O_t = \text{sigm}(Vh_t + b^{(o)}) \tag{16}$$

where, h_{t-1} is hidden state in recurrent neural network, xt is training input data, h_t is hidden layer correspond to xt whereas the O_t is output value, W, U, and V are the weight matrices the bias vector of neural network is denoted by b and the sigm is activation function for transferred the value from the hidden layer into the output vector. It contains a forget gate (f_t), input gate (it), input modulation gate (m_t), output gate (O_t), memory cell (c_t), and hidden state (h_t). The gates are computed:

$$f_t = \text{sigm}(W^{(f)} + X_t + U^{(f)}h_{t-1} + b^{(f)}) \quad (17)$$

$$i_t = \text{sigm}(W^{(i)} + X_t + U^{(i)}h_{t-1} + b^{(i)}) \quad (18)$$

$$m_t = \tanh(W^{(m)} + X_t + U^{(m)}h_{t-1} + b^{(m)}) \quad (19)$$

$$o_t = \text{sigm}(W^{(o)} + X_t + U^{(o)}h_{t-1} + b^{(o)}) \quad (20)$$

where x_t is an input vector, the previous hidden layer is h_{t-1}. The W and U are parameters of weight matrices. For transfer the data from hidden layer into output layer the logistic sigmoid function is employed, *tanh* function is the

Hyperbolic tangent function and b is the bias vector for adjust the cell. Whereas the memory cell (c_t) and the hidden state (h_t) are calculated as

$$c_t = i_t.m_t + f_t.c_{t-1} \quad (21)$$

$$h_t = o_t.\text{tahn}(c_t) \quad (22)$$

The memory cell c_t of the LSTM model contains two main parts, first part, the cell use the information of the previous memory cell c_{t-1} which has modulated by using the forget gate f_t. Second part, the cell use the information of the current input x_t and previous hidden state h_{t-1} which has modulated by using the input modulation gate m_t. The LSTM model employ the forget gate f_t permits to selectively forget its previous memory cell c_{t-1}. The function of input gate is to control the LSTM model to consider the current input, modulation the information of the input gate i_t by using input modulation gate (m_t). Finally, the memory cell is control c_t by using the output gate O_t for transferring to the hidden state h_t.

F. MODEL EVALUATION CRITERIA

To evaluate the performance of the proposed model, MSE, RMSE, MAE and spearman's correlation coefficient (R) metrics are used as evaluation criteria. These metrics have the ability to measure the proposed model by discovering the prediction errors. Most of the evaluation criteria use the differential between the observation and prediction data.

$$MSE = \frac{1}{N}\sum_{k=1}^{n}(x_t - \bar{x}_t)^2 \quad (23)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{n}(x_t - \bar{x}_t)^2} \quad (24)$$

$$MAE = |x_t - \bar{x}_t| \quad (25)$$

$$R = 1 - \frac{\sum(x_t - \bar{x}_t)}{\sum(x_t - \bar{x}_t)} \quad (26)$$

where, x_t is observation data, $\bar{x}_t$ are prediction data and N is the total number of observations data.

IV. RESULTS AND DISCUSSION

In this section, studying, understanding and characterizing network traffic is the main target. The prediction results obtained from the proposed system and the alternative model are presented. Understanding network traffic behaviours is very important for monitoring any type of network. We have proposed the use of machine intelligence to predict network traffic. Real network traffic has been analysed to examine the proposed. Standard evaluation indicators have applied to measure the proposed system. The network traffic data have been divided into testing and training data for validation of the proposed system. The developed forecasting models were validated and tested on a real-time network. The MSE, RMSE,ME and R values were employed to evaluate the proposed time series model and alternative time series models. For the validation of the proposed model to forecast the real time network traffic, we divided data in to 80 training and 20 testing for validation of the proposed model. The testing is considered as future forecasting. The analysis was performed using two algorithms, namely the deep learning LSTM and ANFIS algorithms. The results of the experiments demonstrate that the proposed model could predict the behaviour of network traffic with acceptable and satisfactory results. The results that are obtained from various conventional models are as follows.

A. EXPERIMENTS BY USING4G CELL TRAFFIC FROM KAGGLE

The data has been gathered from a wireless network that connected to 4G network. We have taken the data for one day to test the proposed model. The packets loading for the day was 1254 instances. We have applied the proposed model to predict the loading traffic for that day. The fuzzy C- means was applied to clustering data identifying the similar characters of data and grouped into an individual group for handling overlap data. Due to the network characteristics have a lot of burst and complexity. Weigh exponential smoothing method is applied to predict each clusters individual to obtain five predictors. The Weighted Exponential Smoothing model depends on the smoothing constant; it is then tested with values from 0.1 to 0.9. The MSE performance measure is scrutinised through the use of these parameters. The = 0.5 was appropriate to the data. The five predictors were combined to obtain one prediction. We implemented the alternative, namely LSTM and ANFIS models for predicting network traffic. The log normalisation method is applied to filter the scaling data. Figure 10 shows the five predictors obtain f from WES method.

Table 5 summarizes the empirical results of the proposed model against the existing LSTM model. The implementation has been done in two Scenario, first senior we have applied the proposed model with all data to predict cellular traffic. The results of the proposed model for all data are 0.030,

TABLE 5. Shows the empirical results of the proposed model against the existing LSTM model.

Models	MSE	RMSE	Mean Error	Standard Error (SE)	R (%)
Results of all data					
Proposed model with LSTM algorithm	**0.0301**	**0.1735**	**0.0176**	**0.172**	**98.95%**
LSTM algorithm	0.1919	0.9587	0.0510	0.957	56.17%
Training results					
Models	**MSE**	**RMSE**	**MAE**	**SE**	**R (%)**
Proposed model with LSTM algorithm	**0.0218**	**0.147**	**0.0014**	**0.1478**	**98.67%**
LSTM algorithm	0.247	0.497	0.0122	0.497	76.26%
Testing Results					
Models	**MSE**	**RMSE**	**MAE**	**SE**	**R (%)**
Proposed model with LSTM algorithm	**0.065**	**0.255**	**0.0865**	**0.241**	**97.95**
LSTM algorithm	3.793	1.947	0.2167	1.959	19.10%

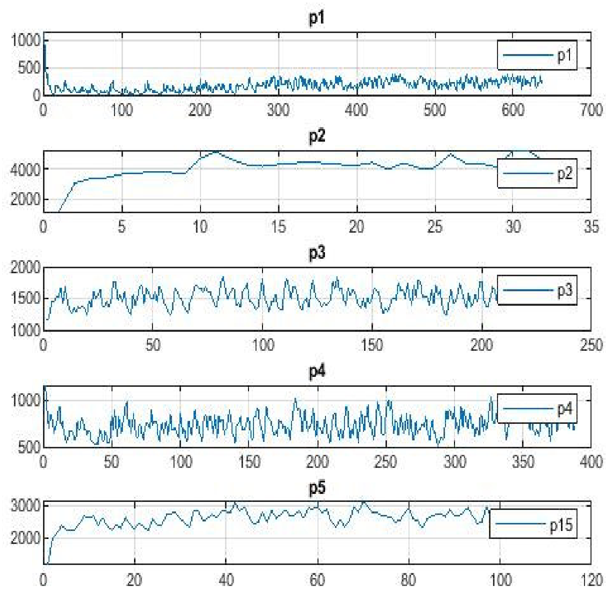


FIGURE 10. Five predictors obtained from WES method for 4Gcell users traffic data.

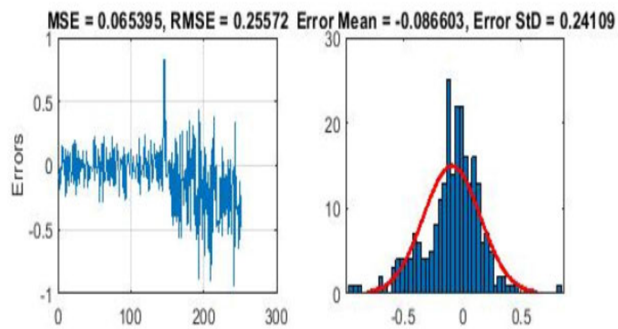


FIGURE 11. Performance of proposed to optimise the LSTM algorithm for training (cellular traffic) data.

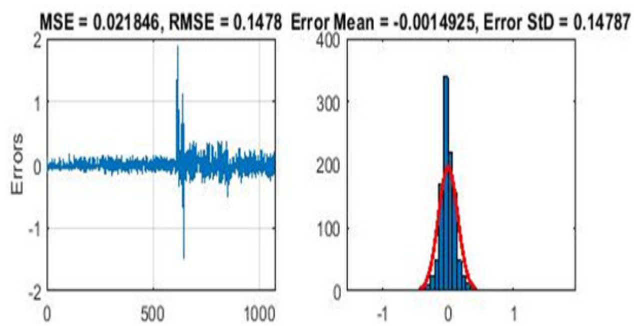


FIGURE 12. Performance of proposed to optimise the LSTM algorithm for testing (cellular traffic) data.

0.173,0.0176 and 0.172 with respect to MSE, RMSE, mean error and Standard Deviation Error (StD).It is observed that the results of the proposed model for prediction all data are more appropriate.

The second scenario, the observation data is divided into 80 training and 20 testing; the testing is considered as future cellular traffic. The results of proposed model are MSE = 0.0215, RMSE = 0.147, mean error = 0.0014 and SE = 0.1478for training, the prediction errors for forecasting future trafficare0.065,0.255,0.0866 and 0.24with respect to MSE, RMSE, mean error and StD. Figures 11 and 12 illustrate how the proposed model forecast future cellular traffic. It is observed that the proposed methodology has optimised the

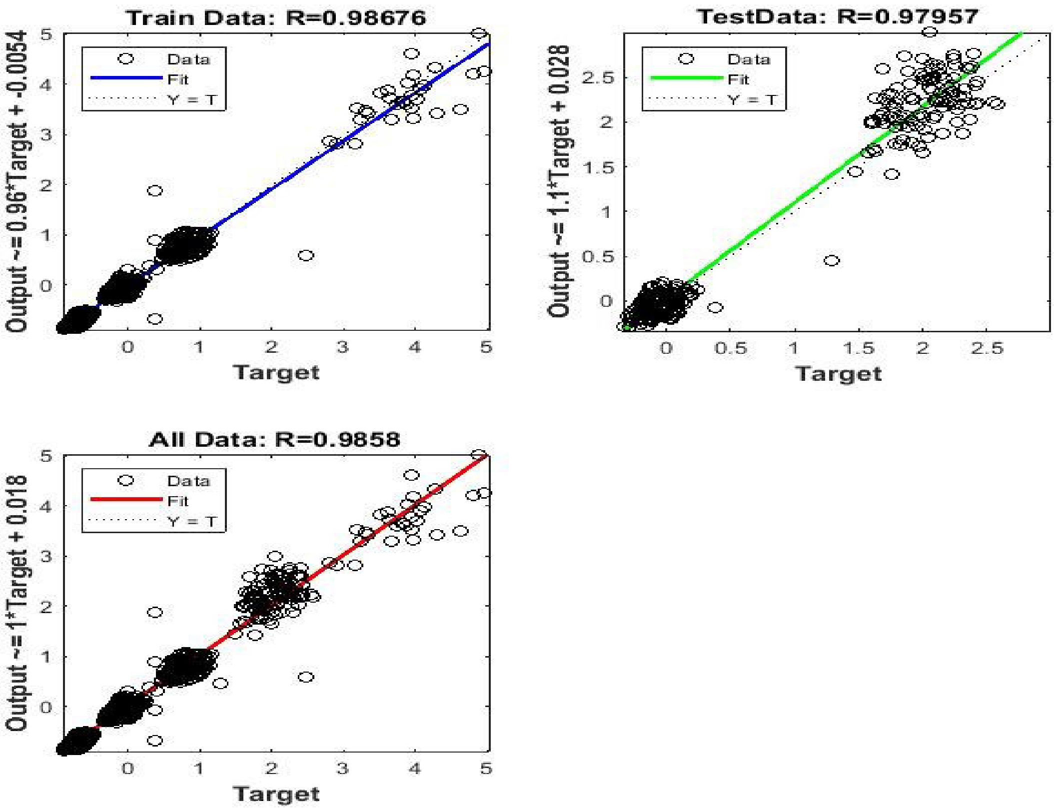


FIGURE 13. The performance of LSTM algorithm for (cellular traffic) data.

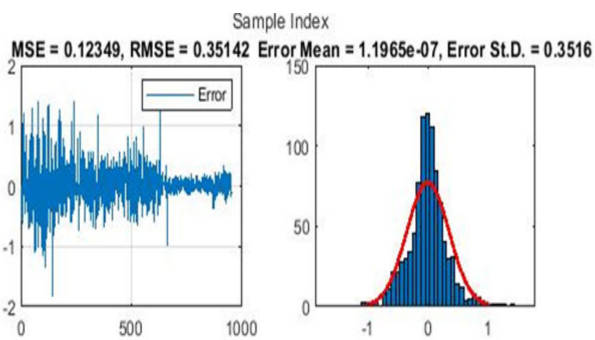


FIGURE 14. Performance of proposed to optimise the ANFIS algorithm for training (cellular traffic) data.

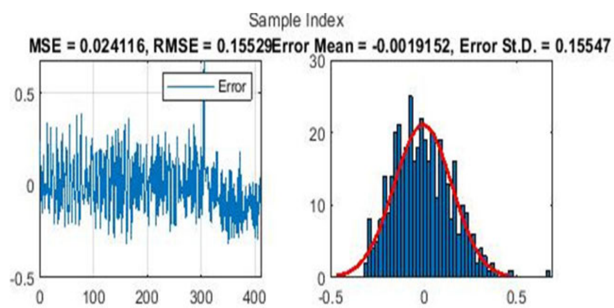


FIGURE 15. Performance of proposed to optimise the ANFIS algorithm for testing (cellular traffic) data.

deep learning LSTM algorithm to predict traffic; the prediction errors have been reduced compared with existing LSTM algorithm. The graphics show how the time series predict model is more close to the observation data. This indicates that the proposed model is more appropriate to predict cellular traffic. The pre-processing steps have improved the existing LSTM time series model. Figure 13 displays the performance of LSTM algorithm by using R metric.

Similarly, the proposed model was applied to improve the ANFIS algorithm to predict cellular traffic. Table 6 demonstrates the prediction results of the proposed model and existing ANFIS time series model. It is observed that there are many differences between ANFIS and improved ANFIS by using machine intelligence. We have implemented the proposed model to all data optimise the ANFIS to predict cellular traffic; it is noted that the proposed model has improved the AFNIS time series model. The result of the proposed model against the existing or prediction all data are0.093,0.306,0.00057 and 0.3062 with respective to MSE, RMSE, mean error and St.D respectively. This is approved that the proposed model is more suitable to enhance the ANFIS time series model for predicting network traffic.

For forecasting future traffic, we have divided data into 80 trainingand20 testing for validating then proposed. The training results of the proposed model are 0.123, 0.351,

TABLE 6. Empirical results of the proposed model against the existing anfis model.

Results of all data					
Models	**MSE**	**RMSE**	**Mean Error**	**SE**	**R (%)**
Proposed model with ANFIS algorithm	**0.0936**	**0.306**	**0.00057**	**0.3062**	**97.05%**
ANFIS algorithm	20.256	1.502	0.221	1.486	54.66%
Training results					
Models	**MSE**	**RMSE**	**MAE**	**SE**	**R (%)**
Proposed model with ANFIS algorithm	**0.123**	**.351**	**1.196-e7**	**0.351**	**96.28%**
ANFIS algorithm	2.076	1.441	4.409	1.441	60.58%
Testing results					
Models	**MSE**	**RMSE**	**MAE**	**SE**	**R (%)**
Proposed model with ANFIS algorithm	**0.0241**	**0.155**	**0.00019**	**0.1559**	**96.78%**
ANFIS algorithm	2.674	1.635	0.736	1.4617	0.70

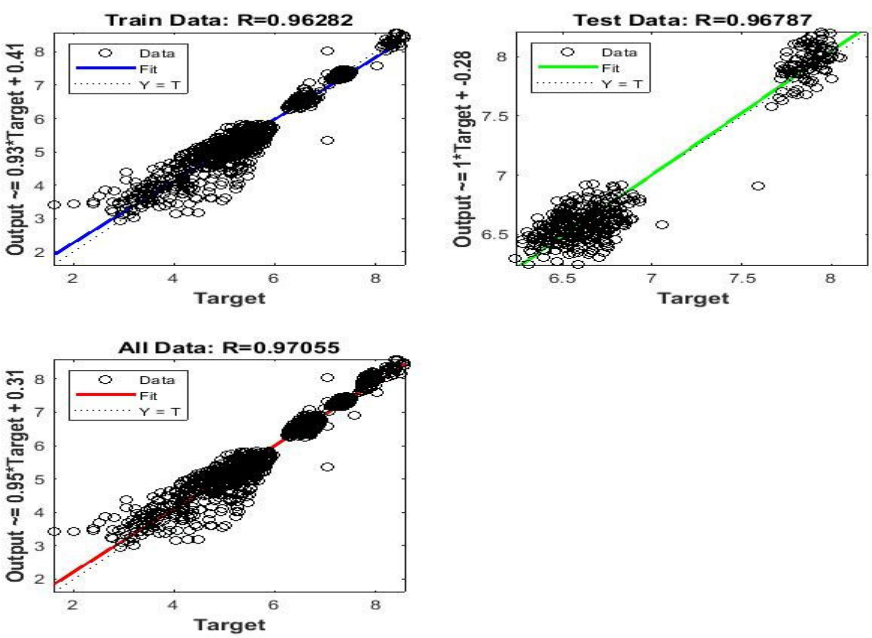


FIGURE 16. The performance of proposed to optimise the ANFIS algorithm for cellular traffic data.

1.196-e7 and 0.351according to indicators metrics MSE, RMSE, mean error and SE respectively. Whereas the testing results of propped for forecasting future traffic are MSE = 0.0241, RMSE = 0.155, mean error 0.00019 and Error StD = 0.1559.Figures 14 and 15 show the stability prediction of the proposed model for training and testing traffic data. It is observed that prediction error very less compared with existing ANFIS for predicting cellular traffic. Figures 16 illustrates the correlation between the observation data and obtained future traffic. The correlation is 96.78% between the observation traffic and future traffic.

B. EXPERIMENTS BY USING MAWI (MEASUREMENT AND ANALYSIS ON THE WIDE INTERNET)

The data has been collected from MAWI for one year on time interval weekly. A new methodology is presented to optimise existing time series models, namely ANFIS and LSTM for prediction loading packets in the network. The fuzzy c-means clustering was used to cluster the data for grouped the similar packets in individual cluster numbers. The five clusters were proposed as input data for obtaining individual predictors by using WES method. The WES method has been implemented to predict five predictors. Figure 17 shows the prediction

TABLE 7. Empirical results of the proposed model against the existing LSTM model by using mawi data.

		Results of all data			
Models	MSE	RMSE	Mean Error	SE	R (%)
Proposed model with LSTM algorithm	**0.225**	**0.475**	**0.0777**	**0.469**	**90.16%**
LSTM algorithm	0.4167	0.6455	0.034	0.645	79.55%
		Training results			
Models	MSE	RMSE	MAE	SE	R (%)
Proposed model with LSTM algorithm	**0.0668**	**0.258**	**0.00281 U8**	**0.2589**	**94.74%**
LSTM algorithm	0.164	0.4060	0.0348	0.4053	91.29%
		Testing results			
Models	MSE	RMSE	MAE	SE	R (%)
Proposed model with LSTM algorithm	**1.0812**	**1.0398**	**0.480**	**0.9313**	**62.25**
LSTM algorithm	1.784	1.3357	0.0298	1.379	20.40%

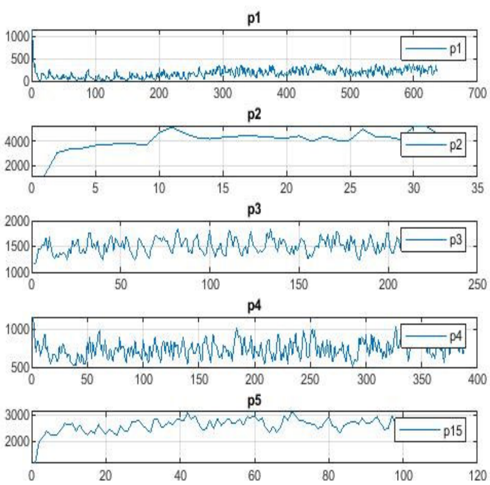


FIGURE 17. Five predictors obtained from WES method by using MAWI data.

results obtain from WES method. Five predictors obtained from five input clusters.

The five predictors are combined to create one predictor; this predictor is considered as input for LSTM and ANFIS time series models. The times series models, namely ANFIS and LSTM, were implemented to predict the future network traffic. Table 7 summarises results of the proposed and existing LSTM algorithm by using MAWI to predict loading the packets. In addition, in this experiment, two scenario have been happed to predict the load packets in network traffic. First senior, prediction all network traffic data by using existing LSTM model and enhanced LSTM. The results of the proposed model for predicting all data are 0.225,0.475, 0.077 and0.469 in terms of MSE, RMSE, mean error and SE respectively. The prediction results are much closed to the observation data according to graphics. In order to forecast future traffic, we have divided the data into 80 training and 20testing. The training results are 0.0668, 0.258, 0.0028 and 0.258 according to the MSE, RMSE, mean error and SE respectively. The testing results are MSE = 1.0812, RMSE = 1.0398, Mean error = 0.480

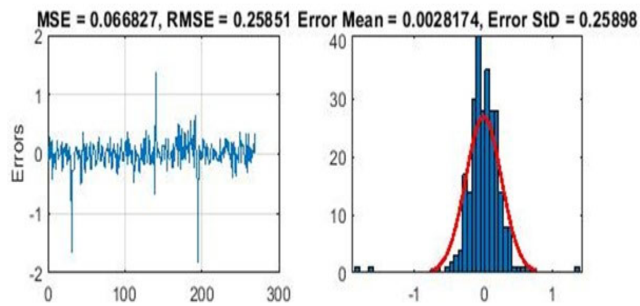


FIGURE 18. Performance of proposed to optimise the LSTM algorithm for training (MAWI) data.

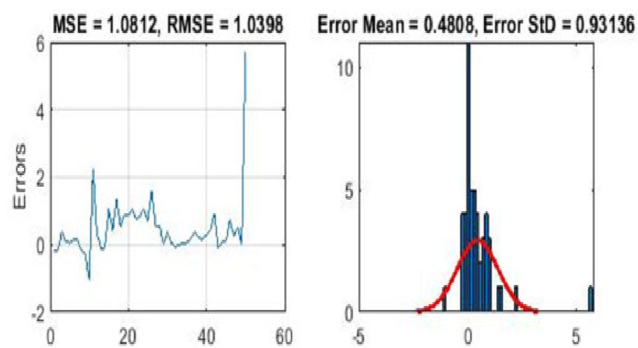


FIGURE 19. Performance of proposed to optimise the LSTM algorithm for testing (MAWI) data.

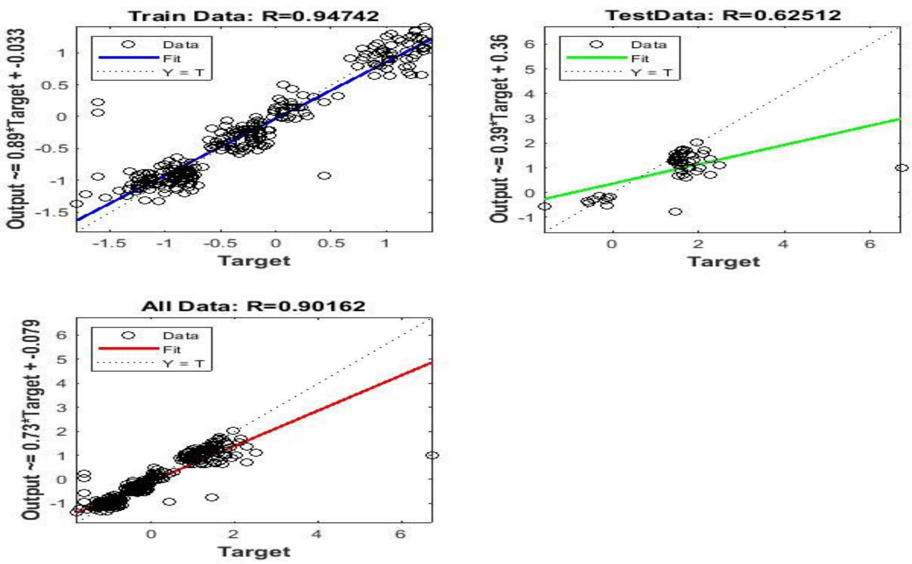


FIGURE 20. The performance of proposed to optimise the LSTM algorithm for (MAWI) data.

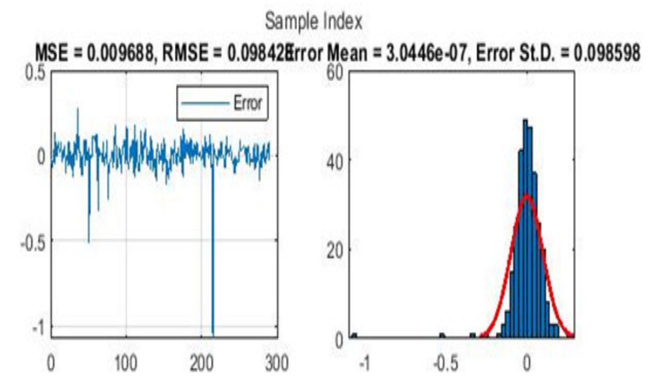


FIGURE 21. Performance of proposed to optimise the ANFIS algorithm for training (MAWI) data.

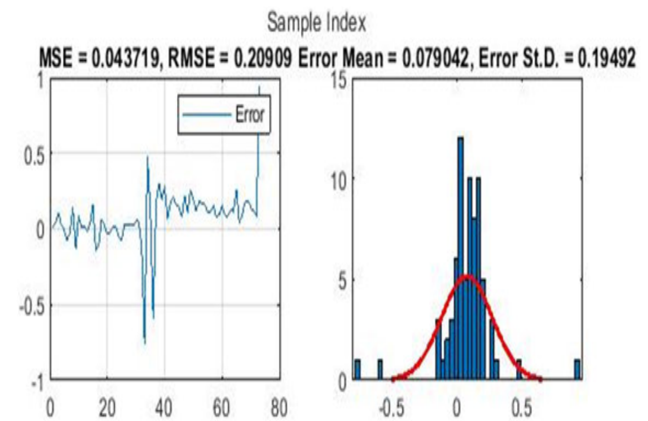


FIGURE 22. Performance of proposed to optimise the ANFIS algorithm for testing (MAWI) data.

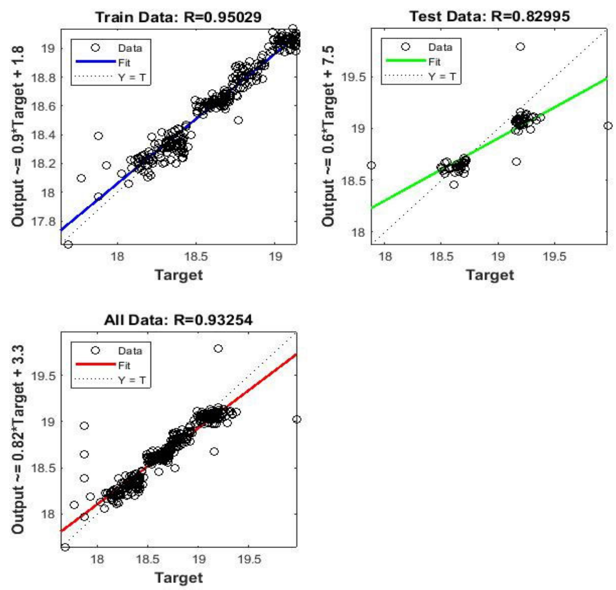
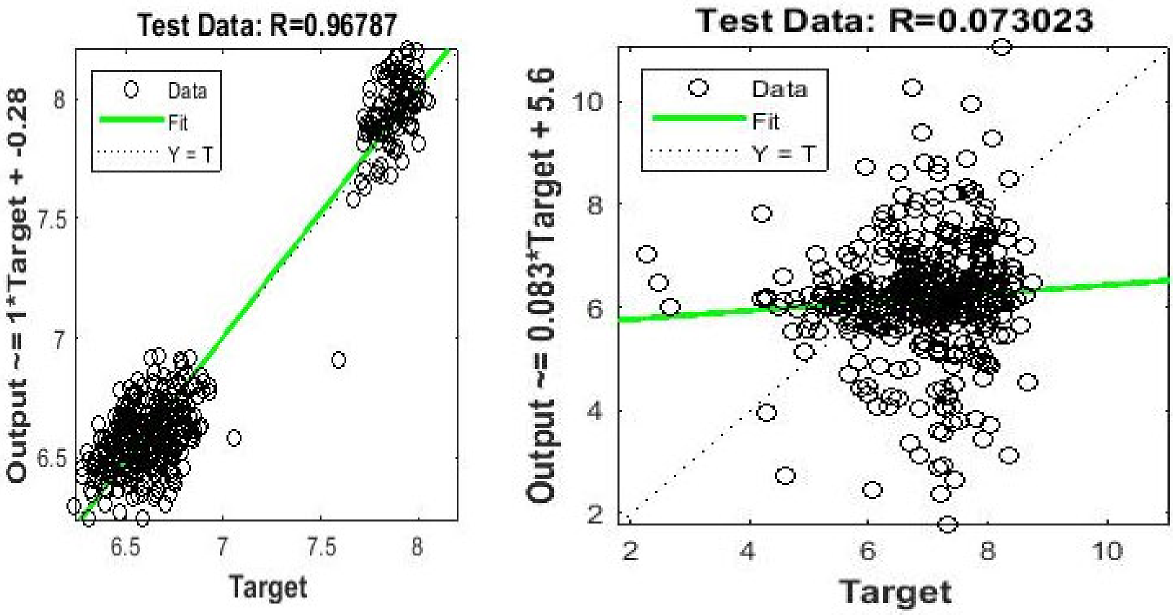


FIGURE 23. The performance of proposed to optimise the ANFIS algorithm (MAWI) data.

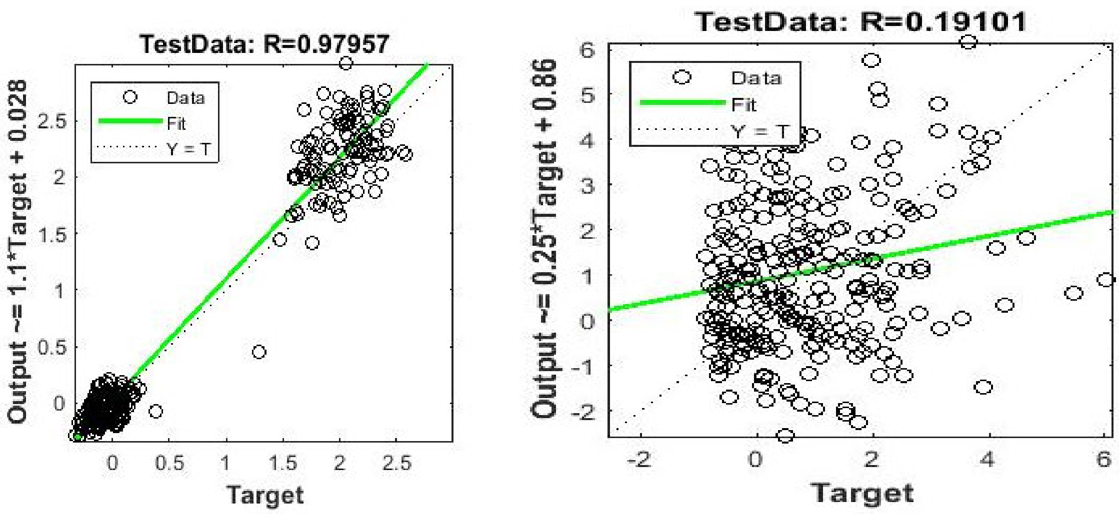
and SE = 0.9313. Figures 18 and 19 show the performance of proposed for training and testing the data. From graphical representation, the proposed model has improved the LSTM time series model for predicting load packets in the network. For finding the percentage correlation between the observation network traffic and prediction results, the R metric is used. We investigated that R = 82.29% for forecast future traffic, it is concluded that the proposed model has improved the prediction network traffic. Figure 20 shows the regression plot of the proposed model to predict loading packets in the network. From the regression plot, it is investigated that there is a robust relationship between the observation data and prediction traffic.

Similarly, table 8 shows the prediction results of proposed against the existing model to predict network traffic. The proposed model has proposed to enhance the ANFIS time



(a) Performance of the proposed model (b) performance of existing LSTM model

FIGURE 24. Shows a comparison between the proposed model and existing LSTM using cellular traffic data.



(a) performance of the proposed model (b) performance of existing ANFIS model

FIGURE 25. Shows a comparison between the proposed model and existing ANFIS using cellular traffic data.

series model to predict flow traffic from a real network. In the beginning, the proposed model employs all the data to predict self similar traffic. The results of the proposed model for predicting all data are 0.0165,0.1285,0.0158 and 0.1277,according to MSE, RMSE, mean error and St.D metrics, respectively

The data has been divided into 80 training and20testingfor forecasting future traffic. The training results of proposed model MSE = 0.0096, RMSE = 0.0984, mean error = -3.044E-07 and SE = 0.0985, whereas testing results are 0.0437, 0.2090, 0.0790, 0.1949 with respective to MSE, RMSE, mean error and SE accordingly. Figures 21 and 22 illustrate the graphical representation of training and testing time series plot for prediction traffic by the proposed model. The prediction results demonstrated that the proposed model has improved the ANFIS algorithm. The correlation indicators have been applied to test the correlation between the prediction results and observation. It is noted that they have the strongest relation to predicting future traffic. Figure 23 shows the correlation between the observation data and traffic by using R metric.

The proposed model has been compared to the existing LSTM and ANFIS time series model to predict network traffic. The comparison has been made by using two real network dataset. We have considered only one indicator metric for comparison: figures 24 (a) and (b) show correlation

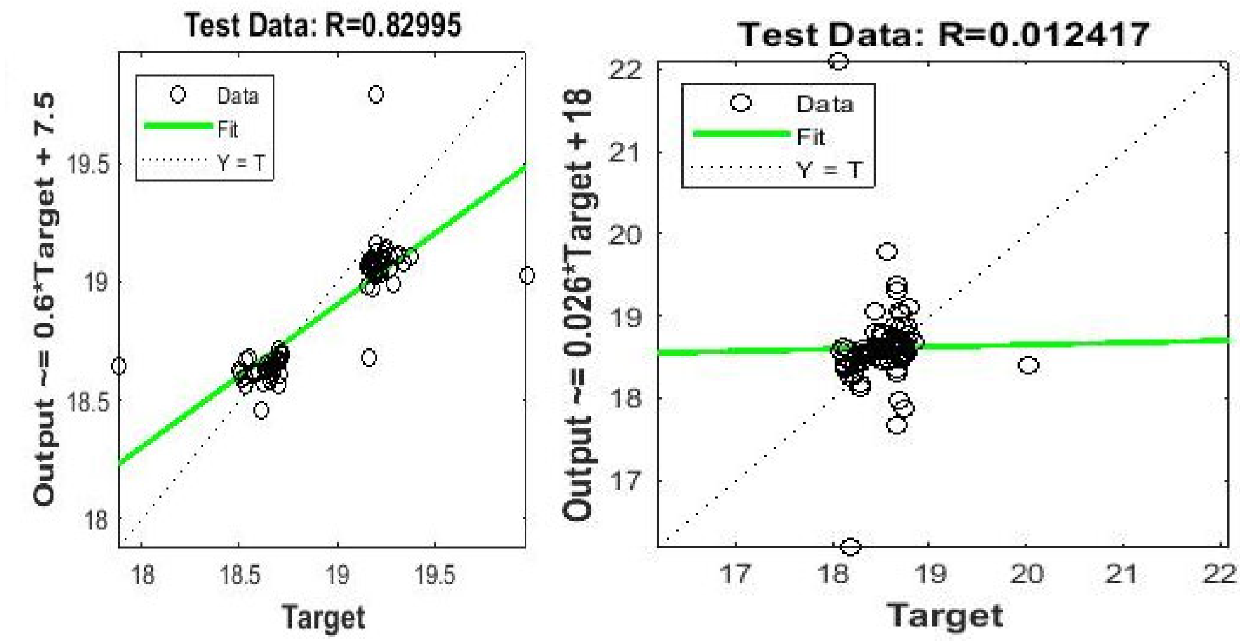
TABLE 8. E empirical results of the proposed model against the existing anfis model by using mawi data.

		Results of all data			
Models	**MSE**	**RMSE**	**Mean Error**	**SE**	**R (%)**
Proposed models with ANFIS algorithm	**0.0165**	**0.1285**	**0.0158**	**0.1277**	**93.25%**
ANFIS algorithm	0.0964	0.3105	0.0150	0.3106	65.70%
		Training results			
Models	**MSE**	**RMSE**	**MAE**	**SE**	**R (%)**
Proposed models with ANFIS algorithm	**0.0096**	**0.0984**	**3.0446e-07**	**0.0985**	**95.02%**
ANFIS algorithm	0.0129	0.1138	-3.1693e-07	0.11407	94.43%
		Testing results			
Models	**MSE**	**RMSE**	**MAE**	**SE**	**R (%)**
Proposed models with ANFIS algorithm	**0.0437**	**0.2090**	**0.0790**	**0.1949**	**82.99%**
ANFIS algorithm	0.4292	0.6551	-0.0752	0.6554	0.12%

TABLE 9. Comparison of different models with proposed model for the prediction of network traffic.

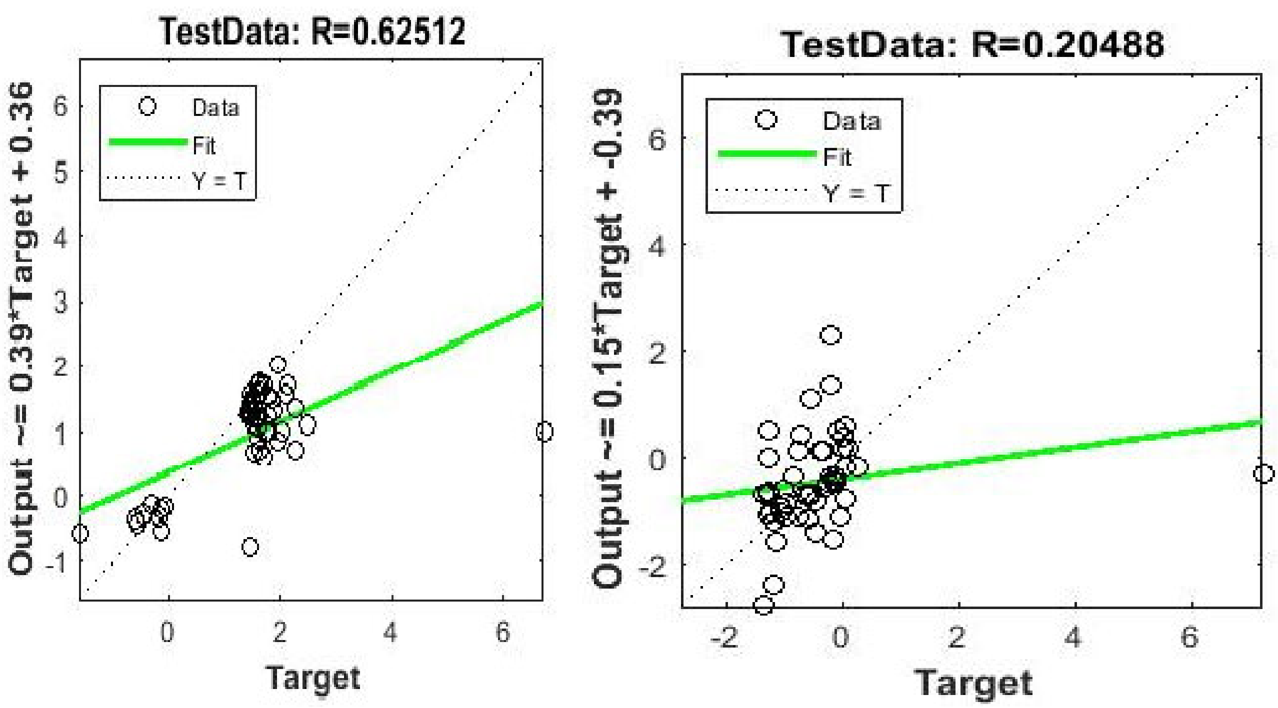
Authors (year)	**Types of data sets**	**Models**	**MSE**	**RMSE**	**MAE**	**R (%)**
Dehai Zhang et al. [67] 2020	Training data	HSTNet	0.0332	0.0476		
Zhihao Wang et al [68] 2019	Training data	LSTM	0.033	0.0459	0.0337	
Pedro Torres et al.[69] 2019	Training data	ARMAX	7.16			
		Navies	6.90			
Alberto Mozo et al. [70] 2008	Training data	CNN	5.33		0.62	
		ARIMA	4.46		0.04	
		ANN	3.20		0.67	
Jingling Li et al [71] 2019	Training data	AR/MA/ARMA	2.2198			
Manish R.Joshi et al. [72] 2016	Training data	ARIMA	0.0217	0.147	0.650	
Existing ANFIS	Training data	ANFIS	2.076	1.441		60.58%
Existing LSTM	Training data	LSTM	0.247	0.0122		76.26%
Existing ANFIS	Training data	ANFIS	0.0129	0.1138		94.43%
Existing LSTM	Training data	LSTM	0.164	0.406		91.29
Propose model (2020)	**Training data**	**Propose model with ANFIS algorithm**	**0.0096**	**0.0984**	**3.0446e-07**	**95.02%**
Propose model (2020)		**Propose model with LSTM algorithm**	**0.0218**	**0.147**		**98.67**

of the proposed model against the existing model. Correlation results are proposed model R = 96.78%, where as the existing LSTM model 0.73% by using cellular traffic data. We have observed that the proposed model has the strongest correlation between the observation data and prediction. Similarly, comparative prediction results between the proposed model and the existing model by using cellular traffic is presented. The correlation results of proposed model is 97.95% and results of existing ANFIS model is 19.10%. Figures 25 (a) and (b) display the comparison between the proposed model and existing ANFIS model to predict cellular traffic. Moreover, we have compared the prediction results between the proposed model and existing LSTM and ANFIS time series models by using MAWI data. Figures 26 (a) and (b) show the performance of the proposed model and existing LSTM, respectively, using MAWI dataset. From graphical representation, the proposed model has the strongest correlation 82.99%, and the existing LSTM



(a) performance of the proposed model (b) performance of existing LSTM model

FIGURE 26. Shows a comparison between the proposed model and existing LSTM using MAWI traffic data.



(a) performance of the proposed model (b) performance of existing ANFIS model

FIGURE 27. Shows a comparison between the proposed model and existing ANFIS using MAWI traffic data.

model is12.41percentage, and it is observed that the proposed is better than the existing LSTM model. Whereas the figures 27 (a) and (b) demonstration the percentage regression between the proposed model and existing ANFIS model to predict loading packets in MAWI data. The correlation results of the proposed model is 62.51%, whereas the existing ANFIS model is 21.48%.It is observed that the proposed model is better. Finally, it is concluded that the proposed methodology has optimised the existing LSTM and ANFIS. time series models. Table 9 shows the results of the existing models against the proposed model.

V. CONCLUSION

The Quality of Service (QoS) is very important in network management, due to predicting the traffic load in the specific network. With increasingly complex and diverse networks, network traffic prediction has become very significant for network management and operation. The proposed research has suggested predicting traffic load for improving network congestion. The time series prediction models are presented to forecast future traffic volume. The proposed model is used to build the regression between the observation volume traffic and future traffic for increasing the performance of the network. Machine intelligence has proposed to enhance time series models for increasing quality of service in the network. The machine intelligence combined from fuzzy c-mean clustering and weighted exponential smoothing method, is used as pre-processing to improve the deep learning LSTM and ANFIS time series models. Two real network traffic traces were used to test and evaluate the proposed model. From the empirical results, the machine intelligence with existing time series models has improved the prediction errors rate. Comparative prediction results between the conventional models with machine intelligence and existing models individual are represented. It is observed that the prediction results of the proposed model are more satisfactory. The proposed machine intelligence provides the optimum results and effectively improves the prediction accuracy of the network traffic. It is concluded that all the objectives that were set at the outset of research have been successfully accomplished with satisfactory results. A suitable time series prediction model assisted by appropriate machine intelligence has been established. A comparative prediction results between the proposed model and existing time series models is presented. It is noted that the proposed model has achieved superior results.

REFERENCES

[1] C. So-In. (2009). *A Survey of Network Traffic Monitoring and Analysis Tool*. St. Louis, MO, USA. [Online]. Available: https://scholar.google.com/scholar?as_q=A+Survey+of+Network+Traffic+Monitoring+and+Analysis+Tool&as_occt=title&hl=en&as_sdt=0%2C31, http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.138.7759&rep=rep1&type=pdf

[2] T. H. H. Aldhyani and M. R. Joshi, "Intelligent time series model to predict bandwidth utilization," *Int. J. Comput. Sci. Appl.*, vol. 14, no. 2, pp. 130–141, 2017.

[3] A. Azari, M. Ozger, and C. Cavdar, "Risk-aware resource allocation for URLLC: Challenges and strategies with machine learning," *IEEE Commun. Mag.*, vol. 57, no. 3, pp. 42–48, Mar. 2019.

[4] C. Qiu, Y. Zhang, Z. Feng, P. Zhang, and S. Cui, "Spatio-temporal wireless traffic prediction with recurrent neural network," *IEEE Wireless Commun. Lett.*, vol. 7, no. 4, pp. 554–557, Aug. 2018.

[5] M. Chen, "Machine learning for wireless networks with artificial intelligence: A tutorial on neural networks," 2017, *arXiv:1710.02913*. [Online]. Available: https://arxiv.org/abs/1710.02913

[6] H. D. Trinh, L. Giupponi, and P. Dini, "Mobile traffic prediction from raw data using LSTM networks," in *Proc. IEEE 29th Annu. Int. Symp. Pers., Indoor Mobile Radio Commun. (PIMRC)*, Sep. 2018, pp. 1827–1832.

[7] Y. Wu, H. Tan, L. Qin, B. Ran, and Z. Jiang, "A hybrid deep learning based traffic flow prediction method and its understanding," *Transp. Res. C, Emerg. Technol.*, vol. 90, pp. 166–180, May 2018.

[8] M. A. Shoorehdeli, M. Teshnehlab, and A. K. Sedigh, "Training ANFIS as an identifier with intelligent hybrid stable learning algorithm based on particle swarm optimization and extended Kalman filter," *Fuzzy Sets Syst.*, vol. 160, no. 7, pp. 922–948, Apr. 2009.

[9] J. Wang, J. Tang, Z. Xu, Y. Wang, G. Xue, X. Zhang, and D. Yang, "Spatiotemporal modeling and prediction in cellular networks: A big data enabled deep learning approach," in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, May 2017, pp. 1–9.

[10] H. K. Choi, "Stock price correlation coefficient prediction with ARIMA-LSTM hybrid model," 2018, *arXiv:1808.01560*. [Online]. Available: http://arxiv.org/abs/1808.01560

[11] C.-W. Huang, C.-T. Chiang, and Q. Li, "A study of deep learning networks on mobile traffic forecasting," in *Proc. IEEE 28th Annu. Int. Symp. Pers., Indoor, Mobile Radio Commun. (PIMRC)*, Oct. 2017, pp. 1–6.

[12] R. Li, Z. Zhao, X. Zhou, J. Palicot, and H. Zhang, "The prediction analysis of cellular radio access network traffic: From entropy theory to networking practice," *IEEE Commun. Mag.*, vol. 52, no. 6, pp. 234–240, Jun. 2014.

[13] G. Lai, W.-C. Chang, Y. Yang, and H. Liu, "Modeling long- and short-term temporal patterns with deep neural networks," in *Proc. 41st Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, Jun. 2018, pp. 95–104.

[14] A. Azzouni and G. Pujolle, "NeuTM: A neural network-based framework for traffic matrix prediction in SDN," in *Proc. IEEE/IFIP Netw. Oper. Manage. Symp. (NOMS)*, Apr. 2018, pp. 1–5.

[15] Broadband Wireless Access Working Group. (2018). *IEEE 802.16m Evaluation Methodology Document*. [Online]. Available: http://ieee802.org/16

[16] S. Skaperas, L. Mamatas, and A. Chorti, "Real-time algorithms for the detection of changes in the variance of video content popularity," *IEEE Access*, vol. 8, pp. 30445–30457, 2020.

[17] O. Cappe, E. Moulines, J.-C. Pesquet, A. P. Petropulu, and X. Yang, "Long-range dependence and heavy-tail modeling for teletraffic data," *IEEE Signal Process. Mag.*, vol. 19, no. 3, pp. 14–27, May 2002.

[18] F. Ashtiani, J. A. Salehi, and M. R. Aref, "Mobility modeling and analytical solution for spatial traffic distribution in wireless multimedia networks," *IEEE J. Sel. Areas Commun.*, vol. 21, no. 10, pp. 1699–1709, Dec. 2003.

[19] K. Tutschku and P. Tran-Gia, "Spatial traffic estimation and characterization for mobile communication network design," *IEEE J. Sel. Areas Commun.*, vol. 16, no. 5, pp. 804–811, Jun. 1998.

[20] L. Xiang, X.-H. Ge, C. Liu, L. Shu, and C.-X. Wang, "A new hybrid network traffic prediction method," in *Proc. IEEE Global Telecommun. Conf. (GLOBECOM)*, Miami, FL, USA, Dec. 2010, pp. 1–5.

[21] G. Xiaohu, S. Yu, W.-S. Yoon, and Y.-D. Kim, "A new prediction method of alpha-stable processes for self-similar traffic," in *Proc. IEEE Global Telecommun. Conf. (GLOBECOM)*, Dallas, TX, USA, Nov. 2004, pp. 675–679.

[22] M. Z. Shafiq, L. Ji, A. X. Liu, J. Pang, and J. Wang, "Geospatial and temporal dynamics of application usage in cellular data networks," *IEEE Trans. Mobile Comput.*, vol. 14, no. 7, pp. 1369–1381, Jul. 2015.

[23] M. E. Crovella and A. Bestavros, "Self-similarity in world wide Web traffic: Evidence and possible causes," *IEEE/ACM Trans. Netw.*, vol. 5, no. 6, pp. 835–846, Dec. 1997.

[24] W. E. Leland, M. S. Taqqu, W. Willinger, and D. V. Wilson, "On the self-similar nature of Ethernet traffic," *IEEE/ACM Trans. Netw.*, vol. 2, no. 1, pp. 1–15, Feb. 1994.

[25] Y. Zhang, M. Roughan, W. Willinger, and L. Qiu, "Spatio-temporal compressive sensing and Internet traffic matrices," in *Proc. ACM SIGCOMM Conf. Data Commun. (SIGCOMM)*, Barcelona, Spain, Aug. 2009, pp. 267–278.

[26] A. Soule, A. Lakhina, N. Taft, K. Papagiannaki, K. Salamatian, A. Nucci, M. Crovella, and C. Diot "Traffic matrices: Balancing measurements, inference and modeling," in *Proc. ACM SIGMETRICS*, Banff, AB, Canada, Jun. 2005, pp. 362–373.

[27] M. C. Falvo, M. Gastaldi, A. Nardecchia, and A. Prudenzi, "Kalman filter for short-term load forecasting: An hourly predictor of municipal load," in *Proc. IASTED ASM*, Palma de Mallorca, Spain, Aug. 2007, pp. 364–369.

[28] R. Li, Z. Zhao, X. Zhou, and H. Zhang, "Energy savings scheme in radio access networks via compressive sensing-based traffic load prediction," *Trans. Emerg. Telecommun. Technol.*, vol. 25, no. 4, pp. 468–478, Apr. 2014.

[29] Y.-C. Chen, L. Qiu, Y. Zhang, G. Xue, and Z. Hu, "Robust network compressive sensing," in *Proc. 20th Annu. Int. Conf. Mobile Comput. Netw. (MobiCom)*, Maui, HI, USA, Sep. 2014, pp. 545–556.
[30] R. Li, Z. Zhao, Y. Wei, X. Zhou, and H. Zhang, "GM-PAB: A grid-based energy saving scheme with predicted traffic load guidance for cellular networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Ottawa, ON, Canada, Jun. 2012, pp. 1160–1164.
[31] N. K. Hoong, P. K. Hoong, I. K. T. Tan, N. Muthuvelu, and L. C. Seng, "Impact of utilizing forecasted network traffic for data transfers," in *Proc. 13th Int. Conf. Adv. Commun. Technol. (ICACT)*, Feb. 2011, pp. 1199–1204.
[32] P. K. Hoong, I. K. T. Tan and C. Y. Keong, "BitTorrent network traffic forecasting with ARMA," *Int. J. Comput. Netw. Commun.*, vol. 4, no. 4, pp. 143–156, Jul. 2012.
[33] N. Sadek and A. Khotanzad, "Multi-scale high-speed network traffic prediction using k-factor gegenbauer ARMA model," in *Proc. IEEE Int. Conf. Commun.*, Jun. 2004, pp. 2148–2152.
[34] Y. Yu, J. Wang, M. Song, and J. Song, "Network traffic prediction and result analysis based on seasonal ARIMA and correlation coefficient," in *Proc. Int. Conf. Intell. Syst. Design Eng. Appl.*, Oct. 2010, pp. 980–983.
[35] Y. Shu, M. Yu, J. Liu, and O. W. W. Yang, "Wireless traffic modeling and prediction using seasonal ARIMA models," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2003, pp. 1675–1679.
[36] E. S. Yu and C. Y. R. Chen, "Traffic prediction using neural networks," in *Proc. IEEE Global Telecommun. Conf. (GLOBECOM)*, Dec. 1993, pp. 991–995.
[37] S. Chabaa, A. Zeroual, and J. Antari, "ANFIS method for forecasting Internet traffic time series," in *Proc. Mediterrannean Microw. Symp. (MMS)*, Nov. 2009, pp. 1–4.
[38] P. Bickel, P. Diggle, S. Fienberg, and U. Gather, *Forecasting With Exponential Smoothing* (Springer Series in Statistics). Springer, 2008, p. 334. [Online]. Available: https://link.springer.com/book/10.1007%2F978-3-540-71918-2
[39] G. P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," *Neurocomputing*, vol. 50, pp. 159–175, Jan. 2003.
[40] J. Wang, Q. Gu, J. Wu, G. Liu, and Z. Xiong, "Traffic speed prediction and congestion source exploration: A deep learning method," in *Proc. IEEE 16th Int. Conf. Data Mining (ICDM)*, Barcelona, Spain, Dec. 2016, pp. 499–508.
[41] A. Azari, P. Papapetrou, S. Denic, and G. Peters, "Cellular traffic prediction and classification: A comparative evaluation of LSTM and ARIMA," in *Discovery Science*. Cham, Switzerland: Springer, 2019, pp. 129–144.
[42] X. Wang, Z. Zhou, F. Xiao, K. Xing, Z. Yang, Y. Liu, and C. Peng, "Spatio-temporal analysis and prediction of cellular traffic in metropolis," *IEEE Trans. Mobile Comput.*, vol. 18, no. 9, pp. 2190–2202, Sep. 2019.
[43] C. Zhang and P. Patras, "Long-term mobile traffic forecasting using deep spatio-temporal neural networks," in *Proc. Mobihoc*, Los Angeles, CA, USA, 2018, pp. 231–240.
[44] V. Sciancalepore, K. Samdanis, X. Costa-Perez, D. Bega, M. Gramaglia, and A. Banchs, "Mobile traffic forecasting for maximizing 5G network slicing resource utilization," in *Proc. IEEE Conf. Comput. Commun. (INFOCOM)*, May 2017, pp. 1–9.
[45] W. Wei and H. W. HuadongMa, "An autoencoder and LSTM-based traffic flow prediction method," *Sensors*, vol. 19, no. 13, p. 2946, 2019.
[46] B. Lu, F. Meng, Y. Zhao, X. Qi, B. Lu, K. Yang, and X. Yan "A linear regression-based prediction method to traffic flow for low-power WAN with smart electric power allocations," in *Proc. 11th Int. Conf. Simulation Tools Techn.* Cham, Switzerland: Springer, Jul. 2019, p. 125.
[47] L. Kuang, X. Yan, X. Tan, S. Li, and X. Yang, "Predicting taxi demand based on 3D convolutional neural network and multi-task learning," *Remote Sens.*, vol. 11, no. 11, p. 1265, 2019.
[48] M. F. Iqbal, M. Zahid, D. Habib, and L. K. John, "Efficient prediction of network traffic for real-time applications," *J. Comput. Netw. Commun.*, vol. 2019, p. 11, Feb. 2019.
[49] M. Roughan, S. Sen, O. Spatscheck, and N. Duffield, "Class-of-service mapping for QoS: A statistical signature-based approach to IP traffic classification," in *Proc. 4th ACM SIGCOMM Conf. Internet Meas.*, 2004, pp. 135–148.
[50] T. Auld, A. W. Moore, and S. F. Gull, "Bayesian neural networks for Internet traffic classification," *IEEE Trans. Neural Netw.*, vol. 18, no. 1, pp. 223–239, Jan. 2007.
[51] S. Khorsandroo, N. R. Md, and S. Khorsandroo, "A generic quantitative relationship to assess interdependency of QoE and QoS," *KSII Trans. Internet Inf. Syst.*, vol. 7, no. 2, pp. 327–346, 2013.
[52] P. Amaral, J. Dinis, P. Pinto, L. Bernardo, J. Tavares, and H. S. Mamede, "Machine learning in software defined networks: Data collection and traffic classification," in *Proc. IEEE 24th Int. Conf. Netw. Protocols (ICNP)*, Nov. 2016, pp. 1–5.
[53] P. Cortez, M. Rio, M. Rocha, and P. Sousa, "Internet traffic forecasting using neural networks," in *Proc. IEEE Int. Joint Conf. Neural Netw.*, Jul. 2006, pp. 2635–2642.
[54] P. Bermolen and D. Rossi, "Support vector regression for link load prediction," *Comput. Netw.*, vol. 53, no. 2, pp. 191–201, Feb. 2009.
[55] Y. Zhu, G. Zhang, and J. Qiu, "Network traffic prediction based on particle swarm BP neural network," *J. Netw.*, vol. 8, no. 11, pp. 2685–2691, Oct. 2013.
[56] Y. Li, H. Liu, W. Yang, D. Hu, and W. Xu, "Inter-data-center network traffic prediction with elephant flows," in *Proc. IEEE/IFIP Netw. Oper. Manage. Symp. (NOMS)*, İstanbul, Turkey, Apr. 2016, pp. 206–213.
[57] *Predict Traffic of LTE Network*. Accessed: 2018. [Online]. Available: https://www.kaggle.com/naebolo/predict-traffic-of-lte-network
[58] *MAWI Working Group Traffic Archive*. Accessed: 2015. [Online]. Available: http://mawi.wide.ad.jp/mawi/
[59] Q. Zhang, T. Gao, X. Liu, and Y. Zheng, "Public environment emotion prediction model using LSTM network," *Sustainability*, vol. 12, no. 4, p. 1665, Feb. 2020.
[60] L. Li, L. Qin, X. Qu, J. Zhang, Y. Wang, and B. Ran, "Day-ahead traffic flow forecasting based on a deep belief network optimized by the multi-objective particle swarm algorithm," *Knowl.-Based Syst.*, vol. 172, pp. 1–14, May 2019.
[61] Y. Gu, W. Lu, L. Qin, M. Li, and Z. Shao, "Short-term prediction of lane-level traffic speeds: A fusion deep learning model," *Transp. Res. C, Emerg. Technol.*, vol. 106, pp. 1–16, Sep. 2019.
[62] Y. Gu, W. Lu, X. Xu, L. Qin, Z. Shao, and H. Zhang, "An improved Bayesian combination model for short-term traffic prediction with deep learning," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 3, pp. 1332–1342, Mar. 2020.
[63] H. Li, Y. Wang, X. Xu, L. Qin, and H. Zhang, "Short-term passenger flow prediction under passenger flow control using a dynamic radial basis function network," *Appl. Soft Comput.*, vol. 83, Oct. 2019, Art. no. 105620.
[64] D. Zhang, L. Liu, C. Xie, B. Yang, and Q. Liu, "Citywide cellular traffic prediction based on a hybrid spatiotemporal network," *Algorithms*, vol. 13, no. 1, p. 20, Jan. 2020.
[65] Y. Huo, Y. Yan, D. Du, Z. Wang, Y. Zhang, and Y. Yang, "Long-term span traffic prediction model based on STL decomposition and LSTM," in *Proc. 20th Asia–Pacific Netw. Oper. Manage. Symp. (APNOMS)*, Matsue, Japan, Sep. 2019, pp. 1–4, doi: 10.23919/APNOMS.2019.8892991.
[66] P. Torres, P. Marques, H. Marques, R. Dionisio, T. Alves, L. Pereira, and J. Ribeiro, "Data analytics for forecasting cell congestion on LTE networks," in *Proc. Netw. Traffic Meas. Anal. Conf. (TMA)*, Dublin, Ireland, Jun. 2017, pp. 1–6, doi: 10.23919/TMA.2017.8002917.
[67] A. Mozo, B. Ordozgoiti, and S. Gómez-Canaval, "Forecasting short-term data center network traffic load with convolutional neural networks," *PLoS ONE*, vol. 13, no. 2, Feb. 2018, Art. no. e0191939, doi: 10.1371/journal.pone.0191939.
[68] J. Li, Y. Zhang, W. Liang, T. Cui, and J. Li, "A spatial information network traffic prediction method based on hybrid model," *Int. J. Electron. Commun. Eng.*, vol. 13, no. 7, pp. 539–549, 2019.
[69] T. H. H. Aldhyani and M. R. Joshi, "An integrated model for prediction of loading packets in network traffic," in *Proc. 2nd Int. Conf. Inf. Commun. Technol. Competitive Strategies (ICTCS)*, Udaipur, India, 2016, pp. 1–6, doi: 10.1145/2905055.2905236.

THEYAZN H. H ALDHYANI was born in Al-Dhalea, Yemen, in 1986. He received the B.Sc. and M.Sc. degrees and the Ph.D. degree in computer science and information technology from NMU University, India, in 2017. He is currently working as an Assistant Professor with the Community College of Abqaiq, King Faisal University, Saudi Arabia. He has published several research articles in the field of computer science and information technology. He has participated in many national and international conferences of the same field. His research interests include machine learning, soft computing, big data, healthcare information, network security, biomedical image processing, network traffic, and the Internet of Things.

MELFI ALRASHEEDI received the Ph.D. degree in operations research (multi-criteria decision analysis) from Brunel University. He is currently an Assistant Professor with the Department of Quantitative Methods, School of Business, King Faisal University. His main research interests include quantitative methods, statistical methods, and data science in medicine, engineering, and social media.

AHMED ABDULLAH ALQARNI received the B.Sc. degree in computer science from King Abdulaziz University and the M.Sc. degree in information technology and the Ph.D. degree in computer science from La Trobe University, Melbourne, Australia. He is currently an Assistant Professor with the Faculty of Computer Science and Information Technology, Albaha University, and the General Supervisor of the training and development of the faculty's staff and students.

MOHAMMED Y. ALZAHRANI received the B.Sc. degree in computer engineering from the Private College of Science, Al Bahah, and the M.Sc. degree in information technology and the Ph.D. degree in computer science from Heriot Watt University, Edinburgh, U.K. He is currently working as the Dean of the College of Computer Sciences and Information Technology, Albaha University, Saudi Arabia. His research interests include data mining, model checking, and cyber security.

ALWI M. BAMHDI received the M.Sc. and Ph.D. degrees in computer science from Heriot-Watt University, U.K., in 2014. He is currently an Assistant Professor with the Department of Computer Sciences, College of Computing, Umm Al-Qura University, Al Qunfudhah, Saudi Arabia. His research interests include mobile ad hoc networks, wireless sensor networks, information security, cyber security, computer vision and simulation, and performance evaluation.