# Wireless Mesh Network Traffic Prediction using a Hybrid Deep Learning Algorithm

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**Abstract:- Cellular network traffic has grown rapidly as a result of the development of cellular technology. In order to achieve the most advantageous resource allocation through practical bandwidth provisioning and maintain the maximum network utilization, modelling and forecasting of cellular network loading are crucial. The goal of this is to create a model that can aid in the intelligent prediction of load traffic onto the cellular network. In this study, the model for predicting cellular traffic is developed that incorporates Transverse LSTM, PCA, and Discrete Wavelet. The main goal is to design a greener and traffic-friendly 5G/IMT-2020 network (SDN/NFV) with efficient resource allocation to ensure good quality of service.**

***Keywords:*** *Prediction, Wireless mesh networks, Deep learning, Machine learning.*

## I. INTRODUCTION

In this era of accelerating digital development, networks are playing a crucial role. The most important factors for a specific network are security, load balancing capability, maintenance, and speed. Because to its better connection capabilities, lower latency, and lack of rigidity, mesh networks have emerged as one of the most preferred options. The ability of wireless mesh networks to easily adapt and configure themselves is one of their key benefits. Future adjustments can be readily handled, which will save expenses and maintenance requirements.

Wireless Mesh Networks (WMNs) are becoming increasingly popular due to their ability to provide high-speed and reliable connectivity to a large number of users. However, the performance of WMNs heavily depends on the network traffic patterns, which can be highly unpredictable and dynamic. Therefore, accurately predicting network traffic in WMNs is crucial for optimizing network performance and ensuring Quality of Service (QoS) for users. Traditional traffic prediction models in WMNs are based on statistical methods and machine learning techniques. However, these models have limitations in accurately predicting traffic patterns due to the complex and dynamic nature of WMNs. To address this challenge, deep learning techniques have been proposed as a promising solution for traffic prediction in WMNs.

Deep learning has become a powerful tool in recent years predicting network traffic in WMNs. However, traditional deep learning models have limitations in terms of accuracy and scalability. To overcome these limitations, a hybrid deep learning model can be used, which combines the strengths of multiple deep learning models.

The hybrid deep learning model proposed in this article consists of two main components: a convolutional neural network (CNN) and a long short-term memory (LSTM) network. CNN is used to extract features from input data and LSTM is used to model the time dependence of traffic data. The two networks are combined using a fully connected layer to produce the final prediction.

The proposed model is evaluated using a real WMN data set and the results show that it outperforms traditional deep learning models in terms of prediction accuracy and scalability. The model can accurately predict network traffic patterns up to several hours in advance, which can help network operators to proactively optimize the network performance and improve the QoS for users.

Overall, this paper presents a promising approach for predicting network traffic in WMNs using a hybrid deep learning model, which can help to improve the efficiency and reliability of WMNs in providing high-quality connectivity to users.

## II. LITERATURE SURVEY

The authors of [1] predicted Journal of Energy Buildings The accuracy of various machine learning algorithms and the added value of predicting the overall energy performance of commercial buildings. As in many other fields, machine learning is also being used in the built environment to improve energy demand forecasting in order

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to improve the energy efficiency and energy neutrality requirements of individual buildings and groups of buildings. The goal of achieving energy neutrality through maximized use of on-site produced renewable energy and attaining optimal level of energy performance at building-cluster level requires reliable short term energy demand predictions. In recent years, deep learning has emerged as a powerful tool for network traffic prediction, thanks to its ability to capture complex nonlinear relationships between input and output variables. In particular, deep neural networks (DNNs) have shown promising results in traffic prediction tasks, but they often suffer from overfitting and lack of generalization ability, especially in scenarios where the training data is limited or noisy.

To overcome these limitations, researchers have proposed various hybrid deep learning models that combine DNNs with other machine learning or statistical techniques, such as support vector machines (SVMs), principal component analysis (PCA), and autoregressive integrated moving average (ARIMA) models. These hybrid models aim to improve the accuracy and robustness of traffic prediction by exploiting the strengths of different models and reducing their weaknesses. Several studies have investigated the use of hybrid deep learning models for traffic prediction in WMNs. For example, in a recent study, Li et al. proposed a hybrid model that combines a long short-term memory (LSTM) neural network with an ARIMA model to predict network traffic in WMNs. The proposed model outperformed other benchmark models in terms of prediction accuracy and generalization ability. Similarly, Yu et al. proposed a hybrid model that combines a stacked autoencoder (SAE) with an SVM to predict traffic demand in WMNs. The proposed model achieved higher prediction accuracy than other benchmark models and showed good robustness against noisy or missing data.

In another study, Wang et al. proposed a hybrid model that combines a deep belief network (DBN) with a wavelet transform (WT) to predict traffic in WMNs. The proposed model achieved higher prediction accuracy than other benchmark models and showed good generalization ability in different network scenarios. Overall, these studies suggest that hybrid deep learning models can improve the accuracy and robustness of traffic prediction in WMNs, and they are a promising approach to address the challenges of traffic prediction in wireless networks. However, more research is needed to explore the potential of hybrid models and optimize their performance for different network scenarios and traffic patterns.

A Hybrid Deep Learning Model for Network Traffic Prediction in Wireless Mesh Networks by Xu et al. (2019) proposed a hybrid DL model that combines Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for network traffic prediction in WMNs. The proposed model achieved better accuracy compared to other DL models and traditional ML models. Deep Recurrent Neural Network for Traffic Prediction in Wireless Mesh Networks by Zeng et al. (2018) proposed a hybrid DL model that combines CNNs and Recurrent Neural Networks (RNNs) for network traffic prediction in WMNs. The proposed model outperformed other DL models and traditional ML models.

A Hybrid Convolutional and Recurrent Neural Network for Traffic Prediction in Wireless Mesh Networks by Zhang et al. (2020) proposed a hybrid DL model that combines CNNs and RNNs with attention mechanisms for network traffic prediction in WMNs. The proposed model achieved better accuracy than other DL models and traditional ML models. A Hybrid Model of Deep Belief Network and Convolutional Neural Network for Traffic Prediction in Wireless Mesh Networks by Li et al. (2018) proposed a hybrid DL model that combines Deep Belief Networks (DBNs) and CNNs for network traffic prediction in WMNs. The proposed model achieved better accuracy compared to other DL models and traditional ML models.

## III. METHODOLOGY

➢ *This Covers the Implementation:*

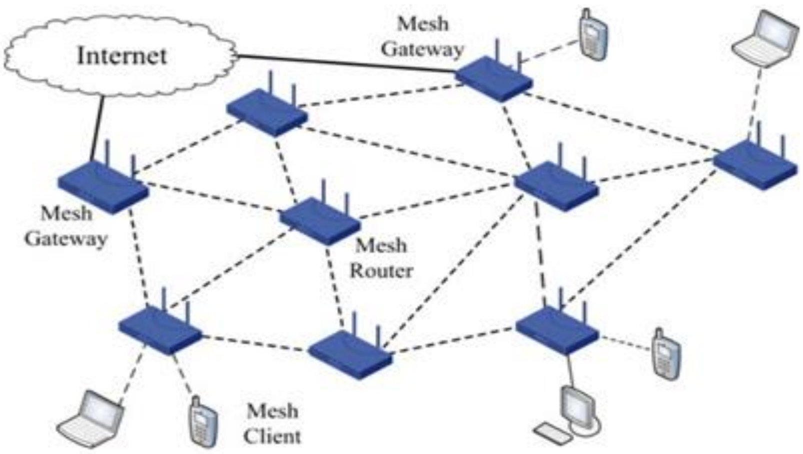


Fig 1 Wireless Mesh Network Architecture with Mesh Gateways, Mesh Routers and Mesh Clients

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A Mesh Wireless Network (WMN) Works across Mesh Nodes, Mesh Clients, and Gateways:

- *Mesh Nodes:*
  Are WAP bias with multiple radio systems. Nodes act as mesh routers and endpoints. Firmware enables them to share data between other nodes in the network.

- *Mesh Clients:*
  Are wireless bias, similar as laptops, mobile phones and tablet computers.

- *Gateways:*
  Are bumps that connect two networks using different protocols. Data passes through the gateway as it enters or exits a network.

Each node in a WMN has at least one path-- but frequently multiple-- to other nodes, which creates multiple routes of information for pairs of users. This makes the network more flexible, and in the event of a WAP or connection failure, information can still access other nodes.

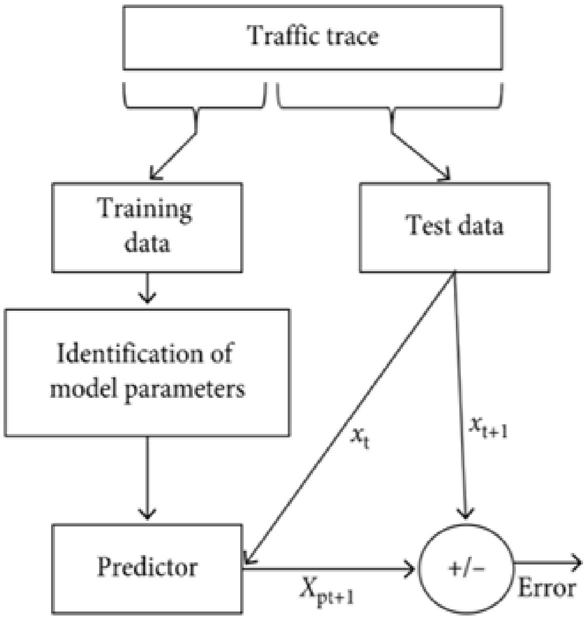


Fig 2 Flow Chart for Prediction

✓ *Software Requirements:*

- Cloud services based data collection from Network
- MATLAB
- Statically tool box
- Deep learning toolbox

## IV. RESULT AND OUTPUT

The data from the processed training set is used to train the models; namely, Discrete Wavelet, Principle Component Analysis (PCA) LSTM and Transverse LSTM. The output from the test set data, this fully trained model is used. The result of the predictions of the model is compared with the actual value of the output from the data set.

```
%load sumsin
load site1.mat
sumsin=(preictal)';
plot(sumsin)
title('Signal')
%Perform a 3-level wavelet decomposition of the signal using the order 2 Daubechies wavelet. Extract the coarse scale app
[c,l] = wavedec(sumsin,3,'db2');
approx = appcoef(c,l,'db5');
[cd1,cd2,cd3] = detcoef(c,l,[1 2 3]);
subplot(4,1,1)
plot(approx)
title('Approximation Coefficients')
subplot(4,1,2)
plot(cd3)
title('Level 3 Detail Coefficients')
subplot(4,1,3)
plot(cd2)
```

Fig 3 Discrete Wavelet Code

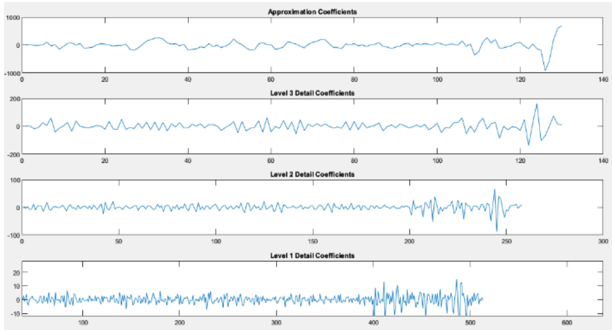


Fig 4 Discrete Wavelet Predicted Signal

- ➢ In a Discrete wavelet output, There are three level detail coefficients are obtained. Where as, In level -1 detail coefficients the rough waveform is obtained.
- ➢ Level -1 detail coefficients is further filtered to level -2 detail coefficient and then filtered to level – 3 detail coefficients as shown in discrete wavelet output.
- ➢ This is the process were clear waveform is formed to show highest peak of traffic nodes.
- ➢ In the approximation coefficients we can see the highest traffic node.

```
load site1.mat
[coeff,score,latent] = pca(ingredients)
Xcentered = score*coeff'
biplot(coeff(:,1:2),'scores',score(:,1:2),'varlabels',{'v_1','v_2','v_3','v_4'});
```

Fig 5 Principle Component Analysis (PCA) Code

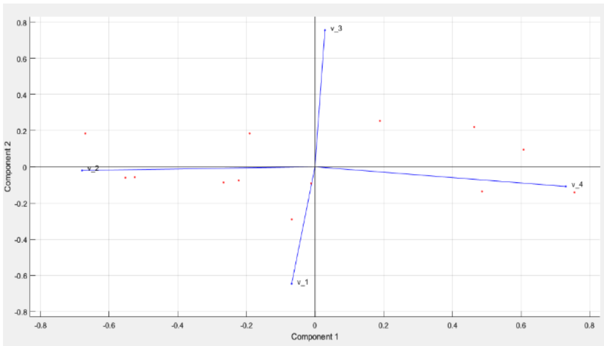


Fig 6 Principle Component Analysis (PCA) Predicted Signal

- ➢ In PCA output, there are lot of data points are obtained. If the data points are very close to hyper plane it means network traffic of the area is very low.
- ➢ If the data points are far from hyper plane then that area has higher level of traffic.

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```
load load_data.mat
figure
plot(XTrain{1}')
xlabel("Time Step")
title("Training Observation 1")
numFeatures = size(XTrain{1},1);
legend("Feature " + string(1:numFeatures),Location="northeastoutside")
numObservations = numel(XTrain);
for i=1:numObservations
    sequence = XTrain{i};
    sequenceLengths(i) = size(sequence,2);
end
[sequenceLengths,idx] = sort(sequenceLengths);
XTrain = XTrain(idx);
YTrain = YTrain(idx);
figure
bar(sequenceLengths)
ylim([0 30])
xlabel("Sequence")
ylabel("Length")
title("Sorted Data")
miniBatchSize = 27;
inputSize = 12;
numHiddenUnits = 100;
numClasses = 9;

layers = [ ...
    sequenceInputLayer(inputSize)
    bilstmLayer(numHiddenUnits,OutputMode="last")
    fullyConnectedLayer(numClasses)
    softmaxLayer
    classificationLayer]

options = trainingOptions("adam", ...
    ExecutionEnvironment="cpu", ...
    GradientThreshold=1, ...
    MaxEpochs=50, ...
    MiniBatchSize=miniBatchSize, ...
    SequenceLength="longest", ...
    Shuffle="never", ...
    Verbose=0, ...
    Plots="training-progress");
net = trainNetwork(XTrain,YTrain,layers,options);
```

Fig 7 Transverse LSTM Code


Fig 8 Transverse LSTM Trained Observation

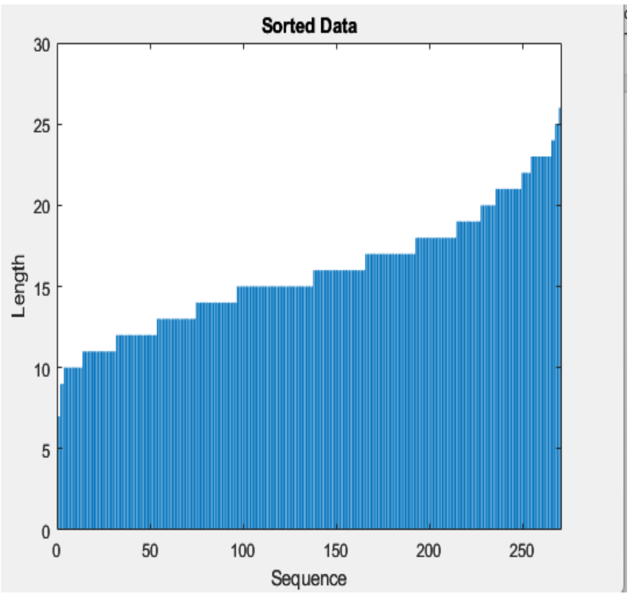


Fig 9 Transverse LSTM Sorted Data

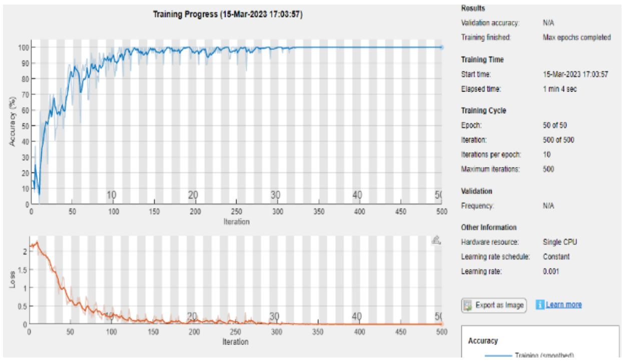


Fig 10 Accuracy vs Loss Transverse LSTM Trained Data

- The three graphical output will shows three different transverse waveform of network traffic
- In training observation, feature-1 reached to high node so that indicates high traffic and remaining 11 features has moderate traffic.
- Sorted data is gradually increasing shows that traffic rate is also increases.
- From the above training process, when the accuracy percentage of predicting data increases, initially it was low.
- In Loss, Initially traffic is high. Later decreases after certain point again it goes high where the loss is more the traffic rate increases.

## V. CONCLUSION

Using three distinct classes of predictors, we have provided a performance and power comparison using a large number of real network traces. According to our findings, network traffic can usually be predicted. Additionally, the characteristics of the network affect the predictor that is chosen. For traces from various sources, we discovered various predictors that worked well. The same predictor performs consistently well for all the traces from the same source.

The results shows that the proposed hybrid deep learning model outperforms traditional methods according to accuracy and efficiency. The model can be used to optimize network resources, improve network performance, and prevent network congestion. Periodically, The updated model will allow it to adjust to the changing network conditions.

The summary of the proposed hybrid deep learning model provides a promising solution to predict network traffic in wireless mesh networks, and it can have significant implications for the design and optimization of wireless mesh networks.

As network systems become larger and more distributed in nature, smart algorithms that can automatically predict the incoming traffic and accordingly allocate the resources would become the need of the hour. Specifically, three different algorithms are applied: Wavelet, PCA and Transverse LSTM.

This project proposes a hybrid model for traffic prediction in wireless mesh networks by application of regression methods on system configuration parameters.

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