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Graph Fick's Neural Networks for Traffic Prediction and Resource Allocation in 6G Wireless Systems

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ABSTRACT
With previously unheard-of speed, capacity, and intelligence, 6G systems have the potential to completely transform connectivity in the rapidly changing wireless communication market. Efficient traffic prediction and subsequent resource allocation are key components of 6G network optimization. This paper presented a novel Graph Convolutional Networks with Energy valley based Fick's Law Allocation (GCN-EVO-FLA) for traffic prediction and optimal resource allocation in 6g wireless system. The dataset was first pre-processed for the traffic prediction. Then the traffic can be predicted using the graph convolutional network and optimized the network parameters using Energy Valley optimizer. In addition, the optimal resource can be allocated using Fick's Law algorithm (FLA). Finally, the performance of the proposed approach can be evaluated with the metrics RMSE, MAE, and Power consumption (PC) and compared with the existing methods. The proposed approach earned 97.32% of , 5.99 of MAE, 15.04 of RMSE and 873 (kWh) of power consumption. When compared to the existing method, the proposed method earned the best performance.

Keywords: Traffic prediction, Resource allocation, wireless system, Graph convolutional network, optimization

1. INTRODUCTION

The introduction of sixth generation (6G) networks promises to be more than just an improvement in the quickly evolving field of wireless communication; rather, it signals a profound change in the way we engage with technology. Beyond the attraction of Ultra-Reliable Low-Latency Communication (URLLC) and terabit-level speeds, 6G is integrating artificial intelligence (AI) [1,2]. Fundamentally, bringing in a new era where connections are sentient entities rather than just data channels. The goal of this combination is to improve both the fundamental design of our smart cities, industries, and larger ecosystems as well as individual digital experiences [3,4]. However, as these networks become more intricate and widespread, their effectiveness depends on a critical skill: real-time traffic analysis. The effectiveness of 6G depends on its ability to fulfil its high expectations and provide users with unmatched experiences among the complexities of changing data traffic [5,6].

The role of traffic analysis is important especially when considering the 6G environment which is revolutionary. The intensity, richness, and variability of traffic on the Internet in the process of approaching the dominance of 6G networks are unprecedented in previous experiments [7,8]. This new generation, 6G, is anticipated to connect trillions of devices from immersive HD VRs to smart home devices, and driverless cars. Now there are many more linked devices contrasted with earlier years, and this means a network of connections with somewhat different traffic rates. The effective traffic analysis is crucial to ensure the liability of carrying out the best performance of the network, resources usage and energy consumptions [9,10]. Due to the amount, diversity, and dynamic of traffic, traditional traffic analysis approaches are inadequate for 6G networks. 6G requires a more advanced, precise, and quick traffic monitoring technique since it adds more types of devices, simultaneous connections, and data flow per device [11-13]. In the realm of Internet of Things (IoT) traffic domain and encrypted application traffic classification, recent advances in network traffic analysis have focused on deep learning architectures, specifically Convolutional Neural Networks (CNNs). Adjusting these techniques to the peculiarities of 6G traffic is still difficult, too [14,15]. This work promises heightened performance in traffic perdition and resource allocation. The major contributions of this work are given below,

- This paper presented a novel Graph Convolutional Networks with Energy valley based Fick's Law Allocation (GCN-EVO-FLA) for traffic prediction and optimal resource allocation in 6g wireless system.
- The dataset is taken for prediction is CDR dataset and first pre-processed the dataset for the traffic prediction by using data cleaning, and normalization.
- Then the traffic can be predicted using the graph convolutional network and optimized the network parameters using Energy Valley optimizer.
- In addition, the optimal resource can be allocated using Fick's Law algorithm (FLA).
- Finally, the performance of the proposed approach can be evaluated with the metrics RMSE, MAE, and Power consumption (PC) and compared with the existing methods.

2. LITERATURE SURVEY

Some of the recent works related to this study are described below,

In 2023, Kim, D. et al, [16] have presented a novel federated learning architecture for network traffic prediction. They employ a linear accuracy estimation model to mathematically investigate and balance the accuracy-cost tradeoff. A range of relaxation methods including mixed-integer nonlinear programming (NP-hard) are used to create the optimization problem. A concave accuracy estimation model is taken into consideration when expanding the problem and a genetic-based heuristic method is suggested to find the suboptimal answer. In 2024, Qin, Z. et al, [17] have presented the spatial-temporal traffic prediction algorithm DenseNet-Transformer for predicting traffic in the network. To capture spatial feature correlations between local traffic in neighboring regions, DenseNet is employed in DenseNet-Transformer. The Transformer component enhances the algorithm's ability to predict temporal patterns by utilizing positional encoding and multi-head attention techniques to learn both short- and long-term temporal relationships. It validates the effectiveness of DenseNet-Transformer through a series of ablation experiments and comparison testing against other algorithms under the same conditions.

The Direction Decide as a Service (DDaaS) approach for network traffic control was proposed by Liu, Y. et al. in 2023 [18]. Its distinct Swarm Learning (SL)-based three-layer service architecture ensures user privacy while facilitating the orderly flow of control instructions and traffic data. Secondly, DDaaS incorporates an enhanced local model and aggregation technique that allows precise forecasting in situations where there are not enough road resources at a single intersection. Third, in order to give signal light switching judgments for quickly evolving ITS, suggest a dynamic traffic control method.

In 2023, Aziz, W.A, et al. [19] have suggested a RNN-LSTM approach to forecast QoS-aware network traffic. With an average accuracy of 96.68%, the model can forecast QoS-aware network traffic for more than 13 hours. A small amount of data obtained by Deep Packet Inspection (DPI) across a live network is used to train and test the model. The prediction algorithm's precision, execution time, and energy usage are evaluated against those of other algorithms. Every QoS class is given network resources by the framework according to its priority and QoS needs. Table 1 shows the state of art of literature survey.

Table 1: State of art of literature survey

Author and reference	Methods	advantage	disadvantage
Kim, D. et al, [16]	NP-FLA	Useful for developing mobile traffic prediction models more cheaply	Federated learning process can become increasingly complex
Qin, Z. et al, [17]	STDNT	Component improves the algorithm's capacity for temporal prediction and more efficiency	DenseNet and Transformer models are known for their high computational requirements.
Liu, Y. et al, [18]	SL-DDoS	The three-layer architecture based on SL is scalable and flexible	Implementing and maintaining a system may require significant effort and expertise
Aziz, W.A, et al. [19]	RNN-LSTM	effective in handling multivariate QoS classes and predicting network traffic accurately	It may require substantial computational resources for training and inference

2.1 Problem statement

Due to high data rates, low latency, and connectivity of devices in the 6G wireless system, the difficulty remains in predicting the traffic density and distribution of resources. It's impracticable to handle distinct applications such as IoT, AR/VR, and autonomous systems by conservative approaches. What is required from this kind of sophisticated networks is a more efficient management of the traffic to predict when there will be more traffic and allocate the resources appropriately to ensure the time and energy consumption are optimized.

3. PROPOSED METHODOLOGY

This research proposed a new approach in GCN with Energy Valleys Fick's Law Allocation, otherwise known as GCN-EVO-FLA, for 6G wireless systems for traffic prediction and resource allocation purposes. The CDR Dataset was used for the prediction, and before making the prediction data cleaning and normalization were is used to predict traffic. Subsequently, the traffic can be predicted by the graph convolutional network, while the Energy Valley optimizer may be employed for fine-tuning of the network. Based on the analyzed criteria, Fick's Law algorithm (FLA) enables the best resource to be allocated. Thus, the efficiency of the recommended approach can be evaluated considering such indexes as Power consumption (PC), Mean Absolute Error (MAE), and Root-Mean-Square Error (RMSE) in comparison with present methods. The figure 1 indicate the work flow of the propose approach.

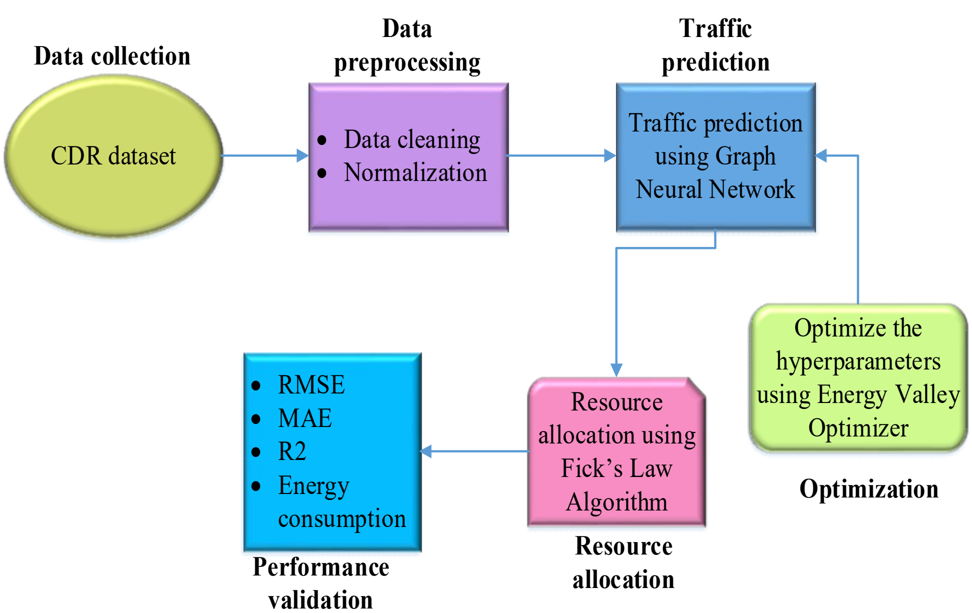


Figure 1: The workflow of the proposed framework

3.1 Dataset Description

This research uses the Telecom Italia Big Data Challenge dataset to perform various experiments. Here, specifically, make use of Milan's Call Detail Records (CDRs) from November 1, 2013, to January 1, 2014. Milan is split up into 100 × 100 grids, with each grid measuring 235 x 235 square meters. The collection contains five different types of CDRs: outgoing, incoming, received, and transmitted SMS as well as Internet. A CDR is generated for the first four categories each time a user places or receives a call or SMS. Every time a user connects or disconnects from the Internet, a CDR is generated if the user transfers more than 5 MB of data or if the connection lasts more than 15 minutes. The temporal interval between the CDRs is ten minutes.

3.2 Data Pre-processing

The data pre-processing is essential for traffic prediction and resource allocation. In a 6G wireless system, preprocessing the Call Detail Records (CDRs) for resource allocation and traffic prediction requires a number of crucial processes to guarantee the data is correct, clean, and suitable for analysis. This is a detailed explanation of the preparation stages:

3. 2. 1 Data Cleaning

The processes which involve arrangement or preparation of data in a proper format to facilitate analysis are referred to as Data Handling. The processes of data cleaning generally are handle missing values, eliminate reduplicate rows and columns, and check for errors.

Handling Missing Values:
Compare actual and planned CDRs side by side and look for the intervals that seem to be missing from the actual record. These maybe because of wrong data acquisition or wrong transfer of the data obtained. For example, if the missing data is expected to be intermediate or have a normal distribution, then impute by using mean values, for skewed data adopt median imputation or use mode imputation.

Removing Duplicates:
It means to discover the record cloning situation that is; sometimes the same CDR might have been entered and stored in the database several times. This process entails the elimination of the many duplicate data values, but at the same time avoiding the loss of any important information. This can be done with identifiers different for each source or checking time stamps of the material in the sources used.

Error Correction: If the data is time stamped also search for records with the wrong timestamp or where the unlikely values have been entered in the fields which contain categorical variables. For the rule/mode to correct the syntactic error, apply domain knowledge. Some examples are: where timestamps are out of range they could be rescaled based on presumed usage patterns.

3.2.2 Min-Max Normalization

The method of min-max normalization is used to scale data to a range, usually [0, 1]. For algorithms that work better when the input features are on a similar scale, this scaling is advantageous. The following is the normalizing formula is given in equation (2).

$$Y_{norm} = \frac{Y - Y_{\min}}{Y_{\max} - Y_{\min}} \tag{2}$$

Where, Y indicates the original value, $Y_{\min}$ and $Y_{\max}$ are the minimum and maximum values of the feature, and Y_{norm} indicates the normalized value. Determine the lowest and maximum values for each feature (such as the quantity of inbound and outgoing calls, SMS messages, and Internet connections) across all grids and time intervals. The scaling bounds are given by this. Throughout the dataset, apply the min-max normalization algorithm to every feature. All feature values are now scaled to the [0, 1] range. Normalization is not applicable if a feature has zero variance, meaning that all values are the same. Either these features should be eliminated or taken care of independently. The min-max normalization can be distorted by outliers. By following this, data cleaning and min-max normalization the CDR Dataset can be pre-processed and prepared for traffic prediction.[20,22]

3.3 Traffic Prediction using Graph Convolutional Network (GCN)

Given the growing complexity of urban road networks, managing spatial information presents a major issue in the context of traffic prediction for a 6G wireless system. Due to their design for grid-like input, like photos, traditional convolutional neural networks (CNNs) struggle with this complexity and may not be able to adequately capture the irregular, graph-like structure of road networks.

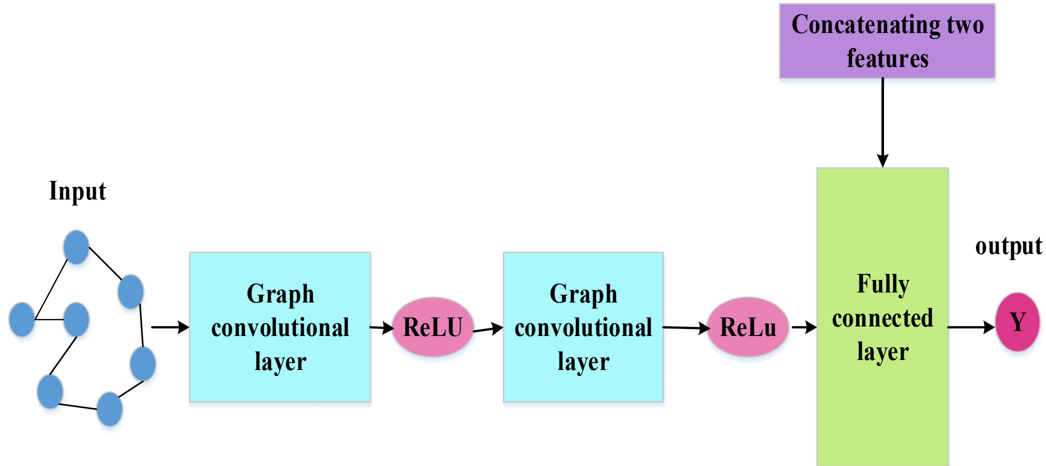


Figure 2: The architecture of the GCN

Graph Convolutional Networks (GCNs) are a solution for traffic prediction, operating directly on graph-structured data. They extend convolutions to graph data, leveraging spatial relationships between nodes to make predictions, addressing the challenge of graph-structured data. The figure 2 shows the architecture of GCN.

The convolution operation in a GCN takes place in the graph domain. To update a node's feature representation, the process aggregates features from nearby nodes. A particular kind of graph convolution called ChebNet can be used to express the fundamental functions of a GCN. But GCN simplifies this by limiting the use to order 1 Chebyshev polynomials. The graph convolution operation in GCN can be represented in equation (3).

$$s' = \widetilde{D}^{-1/2} / \widetilde{M}\widetilde{D}^{-1/2} s.\theta \qquad (3)$$

The adjacency matrix $M + I$, or identity matrix I, has additional self-loops. The degree matrix, or $\widetilde{D}$, is a diagonal matrix in which each element of $\widetilde{D}_{ii}$. The degree of node ii in $A \sim \widetilde{M}$ is represented by i. The convolution kernel's learnable parameters are represented by θ. Nodes' feature matrix is represented by x.

The convolution procedure in the streamlined GCN model is reduced to equation (4).

$$s' = u.\widetilde{D}^{-1/2} / \widetilde{M}\widetilde{D}^{-1/2} s \qquad (4)$$

Where, u is a learnable parameter, and $\widetilde{D}^{-1/2} / \widetilde{M}\widetilde{D}^{-1/2}$ is a normalized adjacency matrix. The GCN uses a stabilization method to prevent problems caused by the adjacency matrix's eigenvalues, such as numerical divergence and gradient explosion in equation (5).

$$s' = u.\widetilde{D}^{-1/2} (\widetilde{M} + I)\widetilde{D}^{-1/2} s \qquad (5)$$

Where, $\widetilde{M} + I$ ensures that the matrix is well-conditioned. By utilizing the graph structure of urban road networks, GCNs provide a strong framework for traffic prediction, facilitating more precise and effective forecasting of traffic conditions in a 6G wireless system. By following these procedures, predict the traffic from the pre-processed data.

3.4 Optimize the hyperparameters of GCN using Energy Valley Optimizer (EVO)

The Energy Valley Optimizer (EVO) [21] is an optimization method which is based on movements of particles in the energy valley searching for the best solution and inspired by nature. Some of the hyperparameters of a Graph Convolutional Network (GCN) that could be tuned with EVO in the case of the studied traffic prediction problem are the number of hidden layers, the learning rate, the number of neurons in each layer, and the dropout rate. EVO adjusts these hyperparameters to control the search towards the configurations that increase the model's predictive accuracy and decrease the error rates since the goal is to enhance the performance of the GCN in traffic prediction tasks. Figure 2 explain the step-by-step process of the EVO.

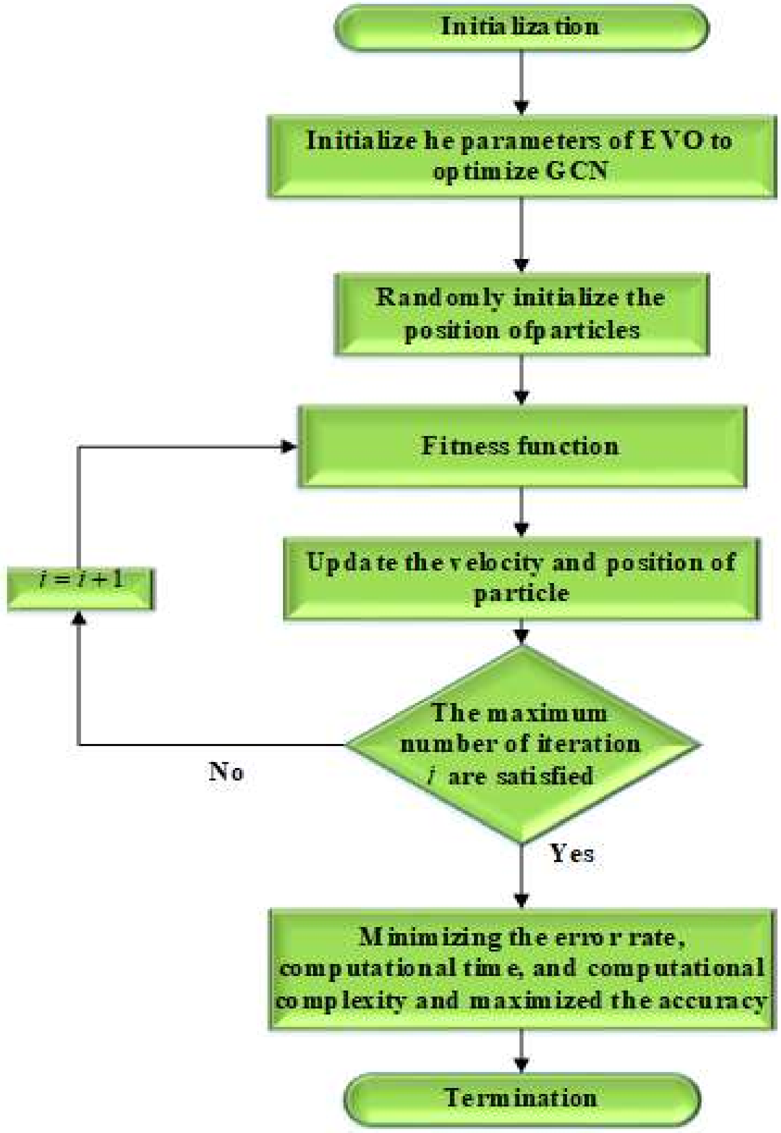


Figure 2: Step-by-step process of EVO

3.5 Optimal Resource Allocation Using Fick's Law Algorithm (FLA)

A 6G wireless network can optimize resource allocation by adapting each phase diffusion, equilibrium, and steady-state to reflect the dynamic processes involved in resource allocation. This can be done by applying the inspiration source, Fick's Law Algorithm . The objective is to maximize resource use while preserving equilibrium between exploration (looking for optimal allocation) and exploitation (using the most well-known allocation).

Step 1 : Initialization

The candidate solutions (C) in the context of 6G wireless networks indicate several approaches to resource distribution for a group of network nodes. Initially, these strategies are created at random, and the best plan at each iteration is regarded as the best use of the available resources given in equation (6)

$$C = \begin{bmatrix} c_{1,1} \cdots c_{1,j} \cdots c_{1,D-1} & c_{1,D} \\ c_{2,1} \cdots c_{2,j} \cdots c_{2,D-1} & c_{2,D} \\ \vdots \quad \vdots \quad \vdots \quad \vdots & \vdots \\ c_{N,1} \cdots c_{N,j} \cdots c_{N,D-1} & c_{N,D} \end{bmatrix} \tag{6}$$

Where j is an identifier for each decision variable, N is the number of candidate solutions, and D is the number of decision variables.

Step 2: Clustering and Transfer Function (TF)

Separate the potential solutions into two groups, denoted as N_1 and N_2, which corresponds to distinct sets of resource allocation tactics. The mechanism of transfer, the difference between exploration and exploitation is determined by TF_t. Here, the dynamic balance between seeking out new approaches and honing the ones that already exist is guaranteed by a nonlinear transfer function given in equation (7).

$$TF_t = \sinh\left(\frac{t}{T}\right)^{0.5} \tag{7}$$

Where, t is the number of iteration, and T is the total number of iterations.

Step 3: Update Resource Allocation Positions

Three stages are used to update the locations of resource allocation strategies: steady-state (exploitation), equilibrium (transition), and diffusion (exploration).

Diffusion Operator (DO)

During the diffusion phase, search space is explored by adjusting resource allocation strategies that show substantial variations. The first wide variance in resource availability and demands across various network locations is simulated in this phase given in equation (8).

$$T_{Do}^{t} = 2 \times TF_t - r \tag{8}$$

where r in [0, 1] is a random number. Adjustments to resource allocation are made in the following direction in equation (9).

$$C_{p,i}^{t} = \begin{cases} from\,region\,i\,to\,region\,j & if\;\; T_{Do}^{t} < rand \\ from\,region\,j\,to\,region\,i & otherwise \end{cases} \tag{9}$$

The number of resources transferred is given by equation (10).

$$NT_{ij} \approx N_i \times r1 \times (X_4 - X_3) + N_i \times X_3 \tag{10}$$

Equilibrium Operator (EO)

The resource allocation plans are adjusted in the equilibrium phase to strike a balance between exploration and exploitation. This shows that the network has reached a point where the demands on its resources are almost equal in all regions given equation (11)

$$C_{p,g}^{t+1} = C_{E,p}^{t} + Q_{E,g}^{t} \times C_{p,g}^{t} + Q_{E}^{t} \times (M_{p,E}^{t} \times C_{E,g}^{t} - C_{p,g}^{t}) \tag{11}$$

Steady State Operator (SSO)

The resource allocation algorithms are optimized to take advantage of the most stable configurations during the steady-state period. In order to maximize efficiency, this step makes sure that the network resources are distributed to their ideal locations in equation (12).

$$C_{p,g}^{t+1} = C_{S}^{t} + Q_{g}^{t} \times C_{p,g}^{t} + Q_{g}^{t} \times (M_{p,E}^{t} \times C_{p,g}^{t} - C_{p,g}^{t}) \tag{12}$$

A balance between exploration and exploitation is guaranteed by the three stages (DO, EO, and SSO). The network can experiment with various resource allocation techniques during the diffusion stage, move from exploration to exploitation during the equilibrium stage, and guarantee that the most promising strategies are implemented during the steady-state stage.

The 6G wireless network can effectively and dynamically distribute resources by implementing these stages, which enable it to adjust to changing demands and sustain peak performance.

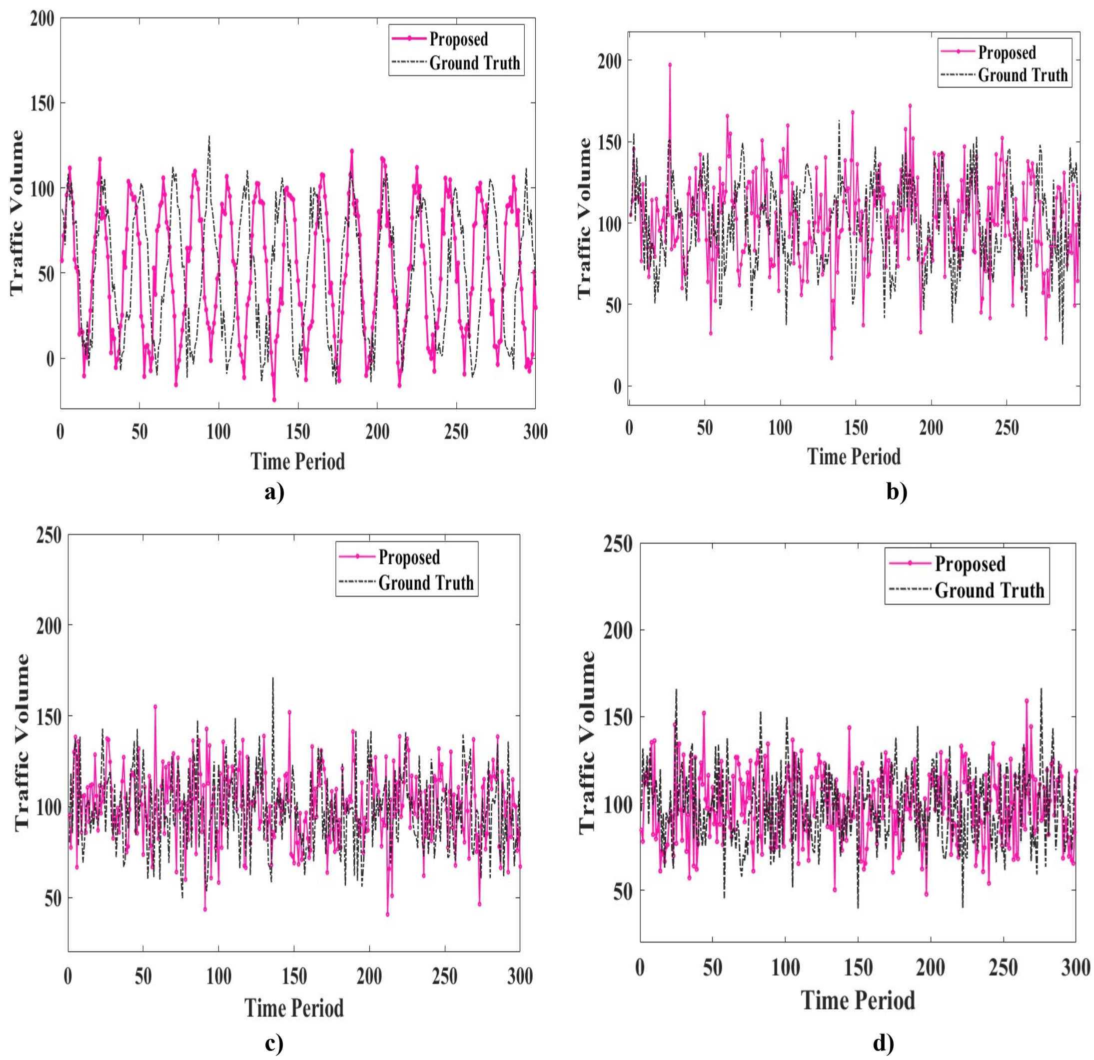
4. RESULT AND DISCUSSION

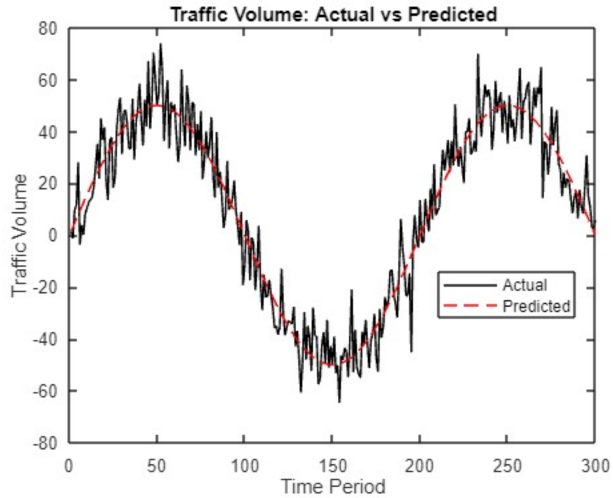
The results and discussion of the proposed GCN-EVO-FLA strategy are presented in this section. The proposed GCN-EVO-FLA approach is tested on the Windows 10 platform and verified in the NS3 platform. Table 2 lists the wireless traffic prediction experiment conditions.

Table 2: Experiment condition

Parameter	Value
training set	80%
Testing set	20%
No of time slots per time period	6
Size of traffic matrices (H,W)	(100,100)
Length of one time slot	10 minutes
Length of one time period	1 hour

The parameters for a study of traffic data are listed in the table 2. It states that 20% will be used for testing and the remaining 80% for instruction. Six ten-minute time slots make up each time period. Given that the traffic data is displayed as 100x100 matrices, it is probable possible that the flow of traffic between 100 origins and 100 destinations is represented.





e)

Figure 4: prediction of a) Incoming SMS traffic b) Outgoing SMS traffic c) Incoming call traffic d) Outgoing call traffic e) Internet Traffic

To give a more natural contrast between the performance of the proposed model and the ground truth result, the predicted outcomes of the model and the target values of the five various types of wireless can be compared to the ground truth result. Figure 4 shows the traffic of cells numbered 51 and 50. For each of the five categories of wireless traffic, the forecast results of our suggested model are, on average, closer to the goal values, as shown by the data shown in Figure 3.

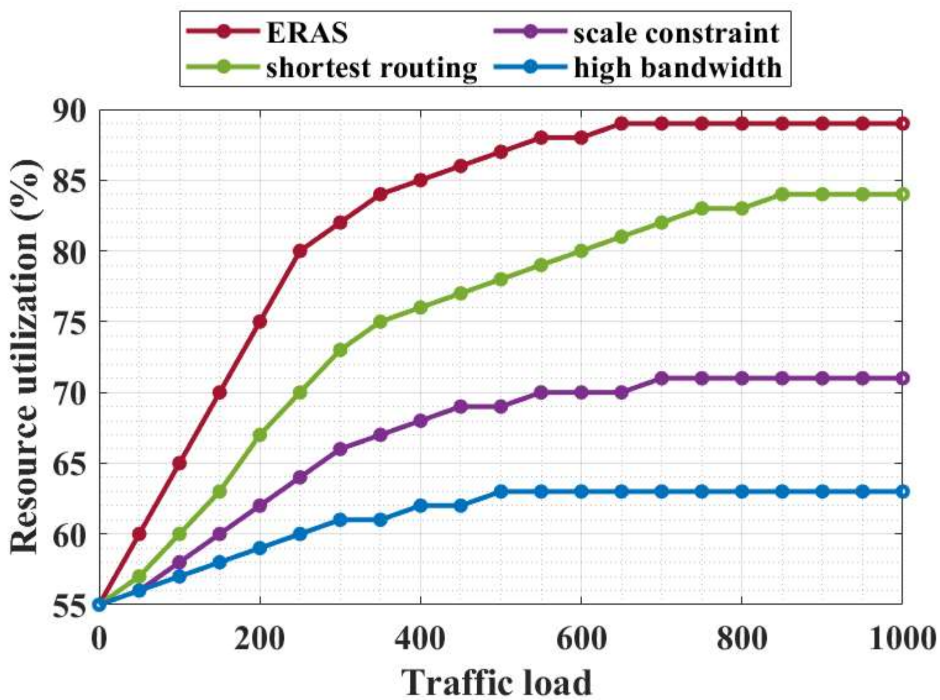


Figure 5: Resource Allocation

Figure 5 shows the resource allocation, there has been a pattern of first growing and then progressively stabilizing with the increase in service intensity. The load balancing virtualization approach uses 8.64% more resources in the stable stage than the shortest routing algorithm. In summary, the proposed efficient Resource allocation source (ERAS) algorithm results in decreased traffic blocking rate and increased resource utilization for end-to-end access service, albeit at the expense of latency.

4.1 Performance Validation

The suggested GCN-EVO-FLA approach is evaluated in a 6g wireless network and on the NS3 platform using the necessary node. A wide range of metrics, including as MAE, RMSE, R^2, and power consumption are utilized to verify the proposed method's efficacy. To demonstrate how the proposed GCN-EVO-FLA strategy performs better than the current method, compare these metrics. NP-FLA [8], STDNT [9], SL-DDoS [10], and RNN-LSTM [11] are the currently used techniques. Table 3 shows the overall comparison of MAE, RMSE, PC and R^2.

Table 3: Comparative analysis of MAE, RMSE, PC and R^2

Methods	MAE	RMSE	R^2	Power consumption (kWh)
NP-FLA	6.5870	21.456	0.873	2992
STDNT	6.2397	19.345	0.8823	2345
SL-DDoS	6.1721	18.344	0.863	1093
RNN-LSTM	6.8923	17.324	0.8934	1224
GCN-EVO-FLA (Proposed)	5.9909	15.045	0.9732	873

5. CONCLUSION

This paper presented a novel Graph Convolutional Networks with Energy valley based Fick's Law Allocation (GCN-EVO-FLA) for traffic prediction and optimal resource allocation in 6g wireless system. In the beginning, the dataset was pre-processed in order to make the traffic prediction. It is therefore possible to make predictions about the traffic by utilizing the graph convolutional network, and the parameters of the network may be tuned by use the Energy Valley optimizer. In addition, the Fick's Law algorithm (FLA) can be utilized to assign the most effective resource. In conclusion, the performance of the suggested method can be evaluated using the metrics RMSE, MAE, and Power consumption (PC), and it can also be compared with the approaches that are currently in use. 97.32% of, 5.99 of MAE, 15.04 of RMSE, and 873 (kWh) of power usage were achieved by the strategy that was given as a recommendation. The performance of the proposed technique was superior to that of the existing method when compared to the existing method. In future, develop and evaluate more advanced machine learning and deep learning models for traffic prediction that can handle the complex, non-linear, and dynamic nature of 6G networks

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