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RESEARCH ARTICLE

Leveraging Global and Local Spatial-Temporal Correlations of Traffic to Improve Congestion Prediction and Routing in 6G Networks

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Abstract – As 6G networks expand, they generate large amounts of data and connect various devices, challenging conventional network management techniques. To address these challenges, a Speed-optimized Long Short-Term Memory (SP-LSTM) model and Reinforcement Learning (RL) have been developed to predict network congestion and optimize routing, respectively, by considering link ID, time, throughput metrics, and congestion levels. However, the SP-LSTM may struggle to adapt to sudden changes in network conditions and capture complex spatial dependencies effectively. This limitation could influence its accuracy in predicting congestion in dynamic 6G networks where spatial and temporal interactions play a crucial role. Improving the model's utilization of spatial and temporal data is vital to enhance its predictive capabilities and address network congestion effectively. Hence, this manuscript introduces a novel Speed-optimized Attention-based Hybrid Graph Convolutional Network-LSTM model (SPAH-GCN-LSTM) to predict network congestion in 6G networks. This model combines global and local spatial correlations in traffic data through global and local spatial-temporal modules to enhance prediction accuracy. The global module utilizes a global correlation matrix and SP-LSTM to capture global spatial-temporal relationship. The local module combines a Fully Connected Layer (FCL), GCN, and SP-LSTM to obtain local spatial relationship. Then, the outputs of these modules are fused using a soft attention strategy to focus on important features for accurate prediction. Moreover, the RL approach is used for dynamic routing based on the predicted congestion conditions and real-time feedback. Finally, experimental results show the superior performance of the SPAH-GCN-LSTM model compared to existing models in 6G networks.

Index Terms – 6G Networks, Network Congestion Prediction, Dynamic Routing, Reinforcement Learning, SP-LSTM, GCN, Spatial-Temporal Correlation, Attention Strategy.

1. INTRODUCTION

In the early stages of networking, static and rigid routing policies sufficed for maintaining stable connections within simpler infrastructures. These traditional paradigms, while effective in the past, are now showing their limitations in addressing the complexities of modern-day networks, especially as the 6G era begins. With 6G's unprecedented data capacity, integration of diverse devices, and emphasis on ultra-low latency, new network management strategies are essential for unlocking its full potential [1]. The dynamic landscape of 6G, supporting advanced real-time applications like remote robotic surgeries and autonomous vehicles, underscores the latency issues, which demand more flexible and intelligent routing systems [2-3].

Monetization and exposure mechanisms are crucial for the 6G's development, mirroring the priorities established during the 5G era. The deployment of 6G networks will only intensify the current focus of communication service providers on monetizing 5G [4]. From the outset, 6G must build upon and expand the exposure and monetization functionalities of its ancestor. Additionally, automation of network tasks is becoming increasingly vital due to the growing complexity of network infrastructures. With more access technologies like new spectrum bands and multiple network slices, manually optimizing these networks is becoming unfeasible [5]. Thus, Artificial Intelligence/Machine Learning (AI/ML) will be integrated as a fundamental element of 6G's design [6]. This AI-driven functionality will replace much of the manual effort involved in network management, from deployment to optimization, and incorporate intent-based management as a key feature [7-8]. However, maintaining ultra-low latency becomes

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significantly more challenging in congested networks. The high volume of data traffic in such situations can introduce delays, especially when rerouting is necessary due to congestion [9]. The latency involved in redirecting data can degrade the performance of latency-sensitive applications. To address this, AI, particularly ML and Deep Learning (DL), offers promising solutions for tackling the complexities of 6G [10-11]. LSTM networks, a type of Recurrent Neural Networks (RNNs), are good at modeling complicated, non-linear dependencies in time-series data. This has changed predictive analytics for 6G network management [12-13].

From these perspectives, Shi et al. [14] have employed LSTM models for traffic prediction, enabling light path reconfiguration in hybrid data center networks. Despite their promise, LSTM networks face challenges such as computational intensity and the difficulty of managing long-term dependencies. To alleviate these issues, Tshakwanda et al. [15] integrated predictive analytics with dynamic routing to optimize resource use and enhance network performance. The two-tier system has been developed by combining SP-LSTM with RL for forecasting and adaptable routing in 6G systems. SP-LSTM predicts network congestion, enabling preemptive measures, while RL optimizes routing paths based on these prediction outcomes. This model leverages constant training, supporting with the progressing nature of 6G systems. It addresses key requirements such as ultra-low delay, consistency, and supervision of heterogeneous network elements. The rapid learning and forecasting capabilities of SP-LSTM make it particularly advantageous in highly dynamic network environments.

1.1. Problem Statement

Recent research has explored local temporal correlation in traffic flow using models like LSTM and SP-LSTM. Instead, spatial correlation also plays a significant role in traffic dynamics, especially in the same direction where congestion at one node can affect surrounding areas. Graph techniques such as GCN and Graph Attention Network (GAN), which analyze spatial correlation, often concentrate on local relationships.

Incorporating global spatial correlation, which considers information from distant nodes, can improve prediction accuracy by providing a broader spatial context. Existing studies may overlook regions with similar traffic patterns that are geographically distant. By incorporating global spatial correlation, researchers can enhance the analysis of spatial relationships in traffic flow. GCN has shown promise in handling non-Euclidean datasets by leveraging network topology to aggregate spatial data. However, using multilayer GCNs may lead to smoothing issues, affecting network congestion predictive analytics. Addressing these challenges is essential to boost the accuracy of predicting congestion (traffic flow) in 6G networks.

1.2. Major Contributions

This manuscript introduces a new hybrid DL model, the SPAH-GCN-LSTM network model, for predicting network congestion in 6G networks. The key contributions of this model include:

- Incorporating global and local spatial-temporal correlations through two main modules:

→ Global spatial-temporal module: It utilizes a global relationship matrix and SP-LSTM network to obtain global spatial-temporal relationships in network traffic data.

→ Local spatial-temporal module: It combines the FCL, GCN, and SP-LSTM to effectively extract local spatial correlations.

- Fusing the outputs from these modules using a soft attention strategy, enables the model to focus on the most significant features and improve the accuracy of network congestion predictions.
- Applying RL-based dynamic routing technique to adjust the routing plan according to the actual response and predicted congestion states.
- Finally, extensive experiments demonstrate that the SPAH-GCN-LSTM model attains better performance in network congestion prediction compared to the conventional models.

1.3. Outline of the Manuscript

Section 2 reviews the literature, Section 3 details the SPAH-GCN-LSTM model, and Section 4 presents its performance. Section 5 concludes this study and recommends upcoming enhancements.

2. LITERATURE SURVEY

Automated forecasting, powered by AI, is revolutionizing network management by leveraging historical data to predict future network conditions. This forward-looking method facilitates data-driven decisions, improving network performance, reliability, and efficiency. This section surveys recent research on the use of AI in 6G networks for network management tasks.

An LSTM-based encoder-decoder network [16] was presented for intelligent traffic prediction using real-world multivariate information from edge μ-packets in a testbed paradigm. The model forecasts the statistical features of the data traffic incoming at the network's edge devices that are supported by cloud driven technology. An Attention-based Spatial-Temporal Graph Neural Network (ASTGNN) [17] was introduced for traffic prediction. A self-attention approach was used in the temporal dimension to obtain the time-based

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interactions in traffic information and global receptive fields for long-term forecasting. A dynamic GCN with self-attention was utilized in the spatial dimension to capture spatial correlations dynamically.

A hybrid model [18] was developed by combining Support Vector Machine (SVM) and Naïve Bayes (NB) to forecast traffic congestion in 5G/6G networks through effective handling of the resources. The gathered information was pre-processed to eliminate unwanted noises and then sent through SVM and NB for learning. The output is stored in the cloud. These trained outputs were then input to the Fused Machine Learning (FML) to achieve higher accuracy and better decision making. A hybrid congestion control strategy using LSTM and SVM [19] was designed for 5G/6G networks. The model addressed slice failure and load balancing in the network, which in turn enhances the decision –making capability of the model. A new Multi-Task (MT) DL model [20] was developed for predicting citywide cellular network traffic. They included a Dual Modular Feature Sharing (DMFS) layer that combines a Convolutional Gated Recurrent Unit (ConvGRU) and 3D Convolutional Neural Network (CNN) to capture long-term spatio-temporal correlations and local spatio-temporal fluctuations in the data. In the MT learning layer, individual tasks predict service-specific traffic data using the FCL.

A high-speed traffic prediction method [21] was developed utilizing ML and RNN. They initially explored a Variable Sampling Rate-Normalized Least Mean Square (VSR-NLMS) flexible forecasting technique to convert time series forecasting archives. Subsequently, a VSR-LSTM was created for real-world network traffic forecasting. Similarly, an Adaptive Time Stepping-GRU (ATS-GRU) was developed [22] for real-world web traffic forecasting in 6G satellite networks. The ATS-GRU method improves network management by maximizing the use of resources according to accurate predictions, while simultaneously decreasing costs and keeping network performance constant. A graph-based training model [23] was introduced for predicting traffic flow in mobile edge computing in 5G/6G systems. In this model, node embedding was learned and fused using Graph Attention network (GAT) and a transformer model was used to forecast truck incidence get into edge systems for the next day.

The DL model with an Efficient Hybrid Attention (EHA) strategy [24] was developed to enhance the analysis of 5G network traffic data by incorporating attention into convolution. They utilized depthwise separable convolution for feature extraction, leading to improved efficiency of the lightweight convolution layer. Table 1 summarizes the above-studied Congestion prediction methods in terms of their merits, and demerits.

Table 1 Comparison of Congestion Prediction Methods

Ref. No.	Methodologies used	Merits	Demerits
[16]	LSTM-based encoder decoder	The model executes straightforward accumulation of data packets which reduces the number of CPU cycles	It cannot capture spatial correlations among data which affecting prediction accuracy
[17]	ASTGNN	It provides more versatile method for simulating the intricate dynamics and recurring patterns found in traffic data over the long term.	It has high predictive errors when dealing with sparse or missing data. In addition, long-term traffic prediction was still a challenge, especially as the prediction interval gets longer.
[18]	SVM, NB, FML	It effectively combined 5G and 6G networks while handling huge amount of data in the network	This model struggles to capture spatial and temporal relationships in the traffic data, leading to reduced accuracy
[19]	LSTM, SVM	Provides adequate bandwidth for every traffic entering the network based on accurate predictions of possible future traffic.	The prediction accuracy is affected by network settings. It did not capture spatial relationships in network traffic data.
[20]	DMFS, ConvGRU, 3D-CNN	This method allows for more efficient and accurate traffic management by capturing the complexities of diverse service demands within a unified framework.	High Mean Absolute Error (MAE) caused by the randomness and burstiness of internet traffic data hindered its performance

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[21]	VSR-LSTM	This approach enhances the precision of real-time traffic forecasting, leading to better optimization of network resource distribution.	This model cannot learn spatial relationships in the data, leading to lower prediction accuracy.
[22]	ATS-GRU	Even under difficult conditions, such as those caused by high-speed mobile connections or network congestion, the model is able to accurately anticipate traffic in real-time by dynamically adjusting sample intervals.	It suffers from high prediction errors attributed to inadequate learning of spatio-temporal relationships
[23]	GAT	Attention Networks improves embedding of inputs and learning graph network, so that the prediction is improved.	Even though provide best prediction accuracy, it is highly dependent on transportation systems, where vehicles frequently enter and leave the network, leading to challenges in maintaining updated and accurate predictions.
[24]	EHA	This method effectively derives feature in the spatio-temporal domain, leading to improved predictive performance.	They faced challenges when dealing with abrupt changes in traffic data, leading to high RMSE and MAE values.

This study emphasizes the importance of selecting the optimal congestion prediction model for making routing decisions in networks with 6G capability. A variety of ML- and DL-based techniques was used to anticipate the congestion. Even so, problems like the limited number of training parameters, the fact that parameter values change in different network environments, and the fact that ML and DL models cannot learn new things make it hard to use congestion prediction techniques. This study presents the SPAH-GCN-LSTM model, which effectively learns geographically and temporally varying parameters to address these issues. Throughput, overhead and resource usage are all improved when two modules of GCN and LSTM are used to improve congestion prediction for route optimization.

2.1. Research Gap

The existing literature on congestion prediction for 6G networks lacks effective integration of global and local spatial-temporal correlations, leading to challenges in adapting to dynamic environments and scalability issues. Attention strategies are underutilized. In addition, congestion prediction and routing optimization are often treated as separate processes. As a result, a more comprehensive, adaptive, and scalable approach is needed to address these limitations and accurately predict congestion in complex 6G network topologies.

3. PROPOSED METHODOLOGY

The SPAH-GCN-LSTM model for congestion prediction in 6G networks is explained in this section. Figure 1 provides a visual representation of the proposed study. The model processes network traffic data through two main modules: a global module (utilizing SP-LSTM and a global correlation matrix) and a local module (employing GCN and FCL). The outputs of these modules are combined using a soft attention strategy to generate predictions for network congestion. These predictions are then used in an RL-based optimized routing system to determine the best routing paths. The model's performance is evaluated to assess its effectiveness in predicting and managing network congestion.

3.1. Preliminaries

This study covers the following relevant definitions:

1. Topology adjacency matrix $A \in \mathbb{R}^{N\times N}$ is a matrix composed of elements a_{ij}, where N is the number of links. The value of a_{ij} is calculated based on the distance between links using a threshold Gaussian kernel, as:

$$a_{ij} = \begin{cases} e^{-d(i,j)^2/\sigma^2}, & d(i,j) < \lambda \\ 0, & d(i,j) \geq \lambda \end{cases} \quad (1)$$

In equation (1), a_{ij} is the neighboring weight between links i and j, $d(i,j)$ represents the distance between links i and j, σ^2 denotes the standard variation and λ defines a threshold.

2. Global correlation matrix $C \in \mathbb{R}^{N\times N}$ defines the spatial association between links i and j. A non-zero value in C_{ij} defines the spatial association degree between links i and j.

3. Spatio-temporal feature matrix $X_T^S \in \mathbb{R}^{T\times S}$ is created using the complete characteristics of traffic flow in the system, where $T = \{1, \dots, t\}$ represents time steps and $S = \{1, \dots, s\}$ represents the total number of links.

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The prediction task is to forecast future congestion (y_{t+1}) according to X_T^S, A, and C at the current moment (t).

$$y_{t+1} = f(X_{t-T}^S, \dots, X_{t-1}^S, X_t^S; A; C) \tag{2}$$

In equation (2), f is the mapping function.

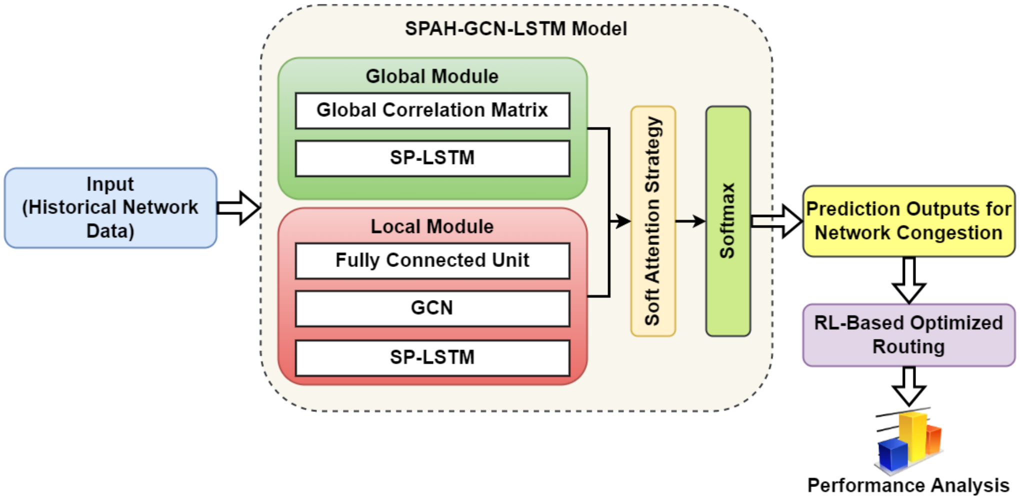

Figure 1 Schematic Representation of the Proposed Study

3.2. Network Congestion Prediction Using SPAH-GCN-LSTM Model

Figure 2 illustrates the architecture of SPAH-GCN-LSTM model, consisting of two modules for local and global spatial-temporal correlation modeling. The global module includes a global graph convolution and SP-LSTM to obtain global spatial characteristics and temporal correlations. The local module comprises the FCL, GCN, and SP-LSTM to extract node features and local spatial correlations. The outputs of both modules are merged and subjected to a soft attention strategy for accurate prediction using the softmax function.

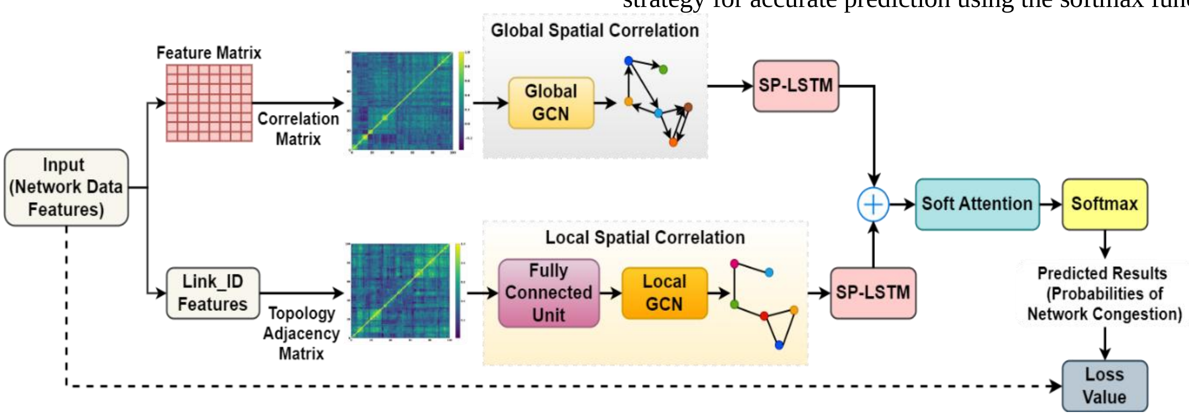

Figure 2 Architecture of SPAH-GCN-LSTM Model for Network Congestion Prediction

3.2.1. Spatial Correlation

This study examines spatial correlation using GCN, focusing on global and local perspectives.

3.2.1.1. Local Spatial Correlation

The Approximate Personalized Propagation of Neural Prediction (APPNP) framework extracts the local spatial relationship of traffic flow by assigning smaller weights to links with more adjacent links during the convolution task. It utilizes PageRank for link feature propagation, encoding characteristics for all source links and increasing the possibility of communication reverse to the source link. This allows the framework to equilibrium the retention of local characteristics and extraction of locality characteristics effectively. The design procedures of this model are given below.

$$Z^{(0)} = H = f_\theta(X) \tag{3}$$

$$Z^{(k+1)} = (1-\delta)\hat{A}Z^{(k)} + \delta H \tag{4}$$

In equations (3) and (4), X is the input and f_θ is a neural network used to extract features of each link. δ represents the percentage of features. Figure 3 shows the spatial relationship of links and their first-order adjacent links (i.e., directly connected through a common node), so k is set to 1. The formulas for extracting local spatial correlation are represented in equations (5) and (6):

$$Z^{(0)} = W_L^{(1)} X + b_L^{(1)} \tag{5}$$

$$GCN_L(X, A) = \sigma\left((1-\delta)\hat{A}Z^{(0)} + \delta Z^{(0)}\right) \tag{6}$$

The FCL extracts link features using weight matrix $\left(W_L^{(1)}\right)$ and bias matrix $\left(b_L^{(1)}\right)$. $GCN_L(\cdot)$ represents the local spatial relationship outcome.

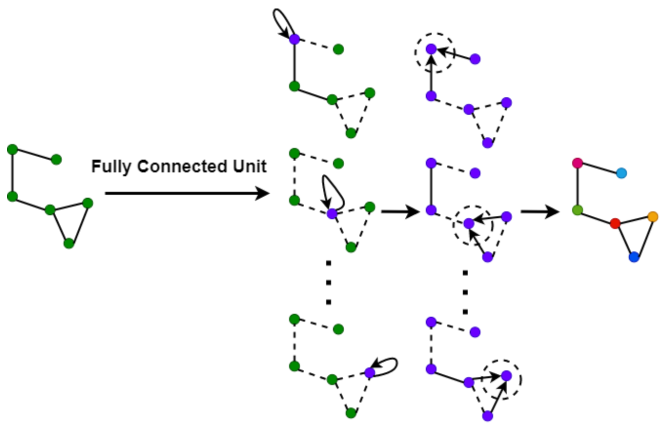

Figure 3 Process of Extracting Local Spatial Correlation Features

3.2.1.2. Global Spatial Correlation

To analyze the relationship between links in a time-series traffic flow data, a Pearson correlation coefficient is utilized. A relationship threshold k is established to determine high-relationship links. If the relationship value exceeds k, it is retained; or else, it is assigned to 0. This process results in creating C, which is then employed to aggregate the features of highly correlated links using the GCN model. The Pearson correlation coefficient is determined by equation (7).

$$C_{ij} = \frac{\sum_{t=1}^{T}\left(x_t^i - \bar{X}_i\right)\left(x_t^j - \bar{X}_j\right)}{\sqrt{\sum_{t=1}^{T}\left(x_t^i - \bar{X}_i\right)^2}\sqrt{\sum_{t=1}^{T}\left(x_t^j - \bar{X}_j\right)^2}} \tag{7}$$

In equation (7) , $X_i = \left(x_1^i, \ldots, x_t^i\right)$ and $X_j = \left(x_1^j, \ldots, x_t^j\right)$ represent the traffic flow features of links i and j, respectively, with $\bar{X}_i$ and $\bar{X}_j$ denoting their respective mean values. C defines a directed weighted graph, illustrated in Figure 4, where links and directions represent influence weights and associations, respectively. By convolving C with the feature matrix, high-correlation link features are aggregated to uncover global spatial relationships. The updated design procedure for the global GCN according to C is as follows:

$$GCN_G(X, C) = \sigma\left(C \times X \times W_G^{(1)}\right) \tag{8}$$

In equation (8), $W_G^{(1)}$ is a weight matrix of the global GCN, $GCN_G(\cdot)$ denotes the global spatial relationship outcome.

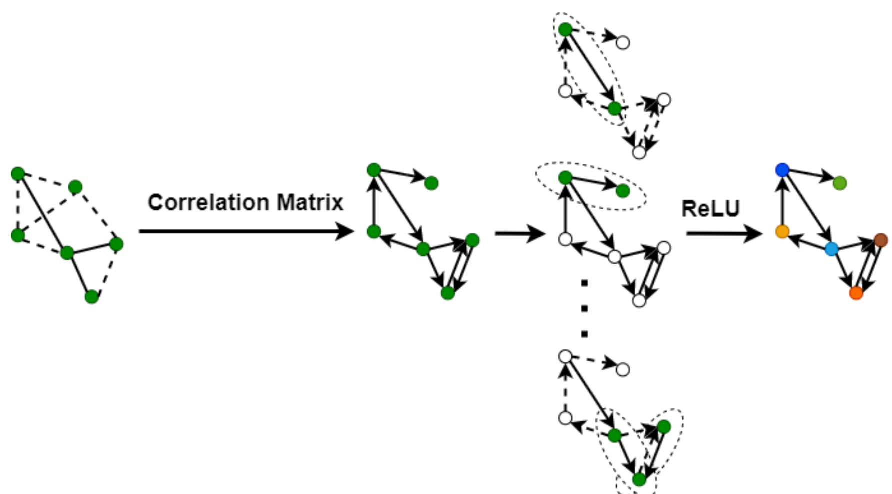

Figure 4 Process of Extracting Global Spatial Correlation Features

3.2.2. Temporal Correlation

SP-LSTM is a popular neural network for forecasting time series data that overcomes issues like gradient explosion and vanishing gradients in RNNs. It makes simpler the traditional LSTM design by uniting the forget and input gates into a unified update gate, improving efficiency similar to GRU while maintaining LSTM's ability to handle long sequences [15]. The local and global spatial relationship outputs are separately input into the SP-LSTM.

For the local spatial relationship outcome, the SP-LSTM design procedures are given below in details from equation (9) to equation (12).

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Update gate, $u_t^l = \sigma(W_u^l[GCN_L(X,A), h_{t-1}^l] + b_u^l)$ (9)

Candidate cell state, $\tilde{C}_t^l = \tanh(W_C^l[GCN_L(X,A), h_{t-1}^l] + b_C^l)$ (10)

Cell state, $C_t^l = u_t^l \times C_{t-1}^l + (1 - u_t^l) \times \tilde{C}_t^l$ (11)

Output gate, $o_t^l = \sigma\left(W_o^l\left[GCN_L(X,A), h_{t-1}^l, \tilde{C}_t^l\right] + b_o^l\right)$ (12)

Where, u_t^l represents the update gate at t, h_{t-1}^l is the hidden state at time $t-1$. W_u^l, W_C^l, and W_o^l are the weight matrices for the update gate, candidate memory, and output gate, correspondingly. Similarly, b_u^l, b_C^l, and b_o^l are the bias vectors for the update gate, candidate memory, and output gate, respectively. $\tilde{C}_t^l$ is the candidate cell state at t, C_t^l is the cell state at t, o_t^l is the output gate at t, and σ represents the sigmoid function.

The SP-LSTM network concatenates the previous hidden layer output h_{t-1}^l with the current input $GCN_L(X,A)$ for a given time series. The data is then transformed into [0,1] using σ to create gate signals u_t^l and $\tilde{C}_t^l$. These gate signals are used to selectively retain or discard information from the previous hidden layer and current input. This allows the SP-LSTM to combine traffic flow information from the previous and current moments, capturing temporal correlations effectively.

Thus, global and local spatial-temporal modules are constructed, as illustrated in Figure 2, to obtain the spatio-temporal relationship of traffic flow information. The global module calculates C using all features, which is then fed into a global spatial relationship module to extract spatial relationship. The output is passed through an SP-LSTM to extract global temporal correlation $\left(h_t^g\right)$. The local module uses a FCL to extract link features and a GCN for spatial feature aggregation. The output is input into an SP-LSTM to extract local temporal correlation (h_t^l). Moreover, the output of these two modules is fused and given to the soft attention module to enhance the model's focus on crucial features and improve prediction accuracy.

3.2.3. Soft Attention Strategy

The soft attention strategy employed in this study is illustrated in Figure 5.

Suppose there are k feature vectors with d dimensions, represented as $h_i = \{h_i^1, h_i^2, \ldots, h_i^d\}, i = 1,2, \ldots k$. The output $\hat{h}$ (also with d dimensions) is computed as a weighted average:

$$\hat{h} = \sum_{i=1}^{k} \alpha_i h_i \quad (13)$$

In equation (13), α_i represents the weight of h_i. To assess the impact of h_i on $\hat{h}$, it needs to be scored. The FCL is utilized to compute a score s_i for each h_i. It is important to mention that functions other than neural networks can also be employed for this purpose. The network's output is as follows:

$$s_i = \Gamma(h_i) = \tanh(\omega^T h_i + b_i) \quad (14)$$

In equations (14), s_i is the correlation coefficient between h_i and $\hat{h}$. After that, the softmax function is utilized to regularize s_i and obtain the final weight α_i as in equation (15):

$$\alpha_i = \text{softmax}(s_i) = \text{softmax}\big(\Gamma(h_i)\big) \quad (15)$$

The attention strategy involves generating a fixed-length embedding $\hat{h}$ of the input sequence h_i by calculating an adaptive weight α_i. The soft attention module output is fed into the softmax classifier to predict network congestion probabilities. During training, the SPAH-GCN-LSTM model uses the following loss function:

$$\mathcal{L} = \|y_p - y_r\| + \beta L_2 \quad (16)$$

In equations (16), L_2 regularization with hyperparameter β is applied to address overfitting. y_p and y_r represent the model's predicted and true values for network congestion, respectively. Additionally, the RL model uses the predicted network congestion data and real-time network conditions [15] to optimize routing paths, reducing latency and improving throughput.

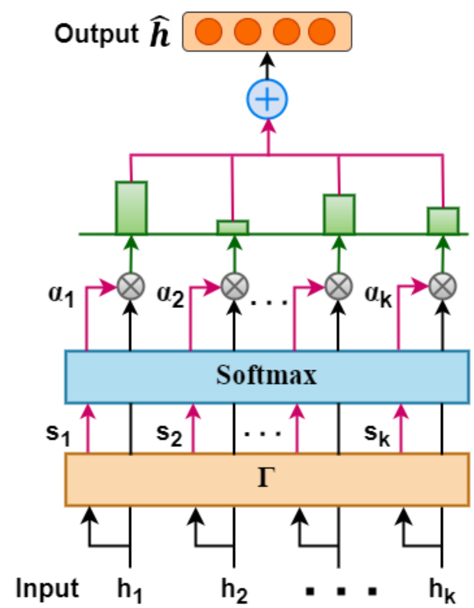

Figure 5 Visual Representation of Soft Attention Strategy

Input: Historical network data

Parameters: //Model weights and biases

$W_L^{(1)}, b_L^{(1)}, W_G^{(1)}, W_u^l, b_u^l, W_C^l, b_C^l, W_o^l, b_o^l, W_u^g, b_u^g, W_C^g, b_C^g, W_o^g, b_o^g$;

Output: Predicted data y_p

1. Begin

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2. Construct the topology adjacency matrix A using equation (1);
3. Calculate the global correlation matrix C using equation (7);
4. Initialize model parameters;
5. for(each time step t ∈ sequence)
6. for(each epoch p ∈ maximum training epochs P)
7. //Local spatial-temporal module
8. Compute local spatial correlation features using equations (5) and (6);
9. Pass them to the SP-LSTM model;
10. Obtain local temporal correlation features;
11. //Global spatial-temporal module
12. Compute global spatial correlation features using equation (8);
13. Pass them to the SP-LSTM model;
14. Obtain global temporal correlation features;
15. Fuse local and global spatial-temporal correlation features;
16. //Soft attention module
17. Assign weights to fused features;
18. Predict network congestion probability using softmax function;
19. Calculate loss using equation (16) and update model parameters with Adam optimizer;
20. end for
21. end for
22. Use trained SPAH-GCN-LSTM model to predict future network congestion;
23. Provide predictions to the RL-based dynamic routing module for optimized routing;
24. End

Algorithm 1 SPAH-GCN-LSTM Training Process

4. RESULTS AND DISCUSSION

The proposed model demonstrates the advantages of proactive AI/ML systems for optimizing resources and enhancing network performance in the context of 6G technology. Through the utilization of the SPAH-GCN-LSTM network and RL, this study facilitates accurate modeling of network patterns, prediction of congestion, and prevention of disruptions. Real-time data analysis and intelligent routing choices contribute to maintaining high network performance, handling extensive data loads, and facilitating rapid routing decisions within 6G networks.

4.1. Network Topology

The Python language tailors the network topology for 6G networks, incorporating nodes, links, and key elements. These elements include the AMF for access and mobility management, the SMF for session controlling and traffic tuning, the UPF for managing user-level traffic, and the gNB as the base station for signal transfer, delivery, and radio resource supervision. Various mobility models are employed to user components to execute real mobility situations. Technologies like massive MIMO, mmWave communications, web slicing, edge systems, SDNs, and VNFs are incorporated to enable the assessment of system control and adjustment procedures [15]. To enhance realism, the experimental setup includes realistic traffic patterns and diverse traffic types, which mimic the characteristics of emerging 6G uses and facilities, such as ultra-high-definition audiovisual flooding, IoT interactions and mission-essential infrastructures.

4.2. Dataset

The dataset created from the network topology includes essential attributes such as link_ID, period, moving_mean_throughput, instant_throughput, and time_mean_throughput. The link_ID identifies network connections between nodes, period tracks temporal data, moving_mean_throughput shows average throughput over period, instant_throughput displays real-time performance variations, and time_mean_throughput indicates time-based average throughput. This dataset can be found on GitHub at https://github.com/pmushidi2/AI-PoweredPredictive-Analytics-and-Dynamic-Routing.git. In this experiment, 80% features are utilized for training and a residual 20% are utilized for testing.

4.3. Parameter Settings

The model's performance is validated through multiple neural network experiments, resulting in optimized parameters listed in Table 2.

Table 2 Parameter Settings

Parameters	Range
Number of hidden layers in GCN	2
Hidden dimension	16
Number of LSTM units	3
Training rate	0.0001
Dropout rate	0.5

Number of epochs	120
Batch size	64
Optimizer	Adam
δ	0.82
Correlation threshold, *k*	0.6

The tests were conducted on a desktop with an Intel® Core™ i5-4210 CPU @ 3GHz, 8GB RAM, and a 1TB HDD running Windows 10 64-bit. To ensure a fair comparison, both the proposed and existing models are tested using the dataset described in Section 4.2.

4.4. Performance Analysis for Network Congestion Prediction

The efficiency of predicting network congestions using the SPAH-GCN-LSTM model is measured and evaluated against existing models such as SP-LSTM [15], ASTGNN [17], VSR-LSTM [21], and ATS-GRU [22]. From Figure.6 to Figure 10 presents the results of the SPAH-GCN-LSTM model compared to other models for network congestion prediction.

- Prediction accuracy: It is calculated by in equation (17)

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \times 100 \quad (17)$$

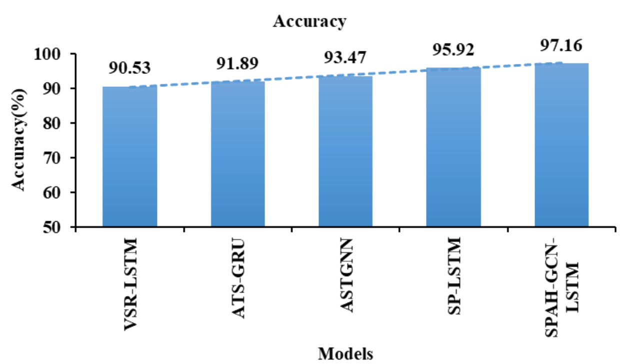

Figure 6 Comparison of Accuracy for SPAH-GCN-LSTM with Existing Models

Figure 6 displays the prediction accuracy results for SPAH-GCN-LSTM compared to existing models. The SPAH-GCN-LSTM outperforms other models in predicting network congestion conditions. It shows an accuracy improvement of 7.32%, 5.74%, 3.95%, and 1.29% over VSR-LSTM, ATS-GRU, ASTGNN, and SP-LSTM, respectively.

- Mean Absolute Error (MAE): It represents the mean absolute dissimilarity between estimated and observed values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (18)$$

In equation (18), n denotes total observations, y_i and $\hat{y}_i$ denote the observed and predicted values of i^{th} data, respectively.

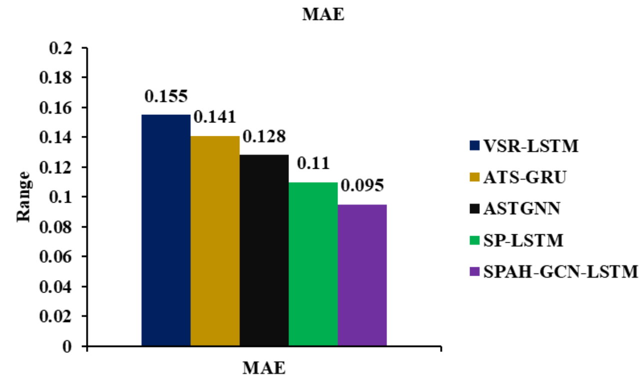

Figure 7 Comparison of MAE for SPAH-GCN-LSTM with Existing Models

Figure 7 plots error metrics MAE for SPAH-GCN-LSTM with existing models. The results show that SPAH-GCN-LSTM outperforms other models in reducing error values for predicting network congestion. Specifically, the MAE is reduced by 38.71%, 32.62%, 25.78%, and 13.64% compared to the VSR-LSTM, ATS-GRU, ASTGNN, and SP-LSTM, respectively.

- Root Mean Square Error (RMSE): It measures the mean squared dissimilarity between estimated and observed values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (19)$$

In equation (19), n denotes total observations, y_i and $\hat{y}_i$ denote the observed and predicted values of i^{th} data, respectively.

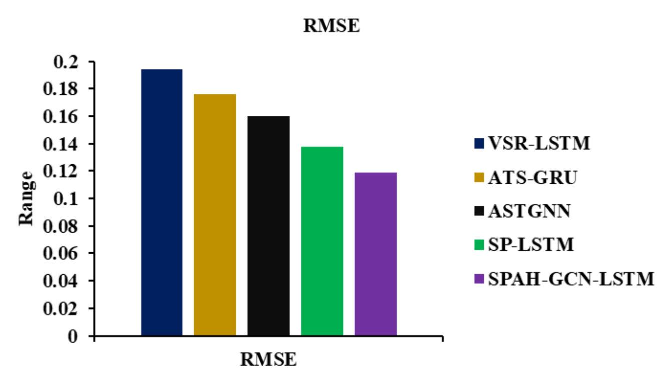

Figure 8 Comparison of RMSE for SPAH-GCN-LSTM with Existing Models

Figure 8 plots error RMSE for SPAH-GCN-LSTM with existing models. The results show that SPAH-GCN-LSTM

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outperforms other models in reducing error values for predicting network congestion. The RMSE is reduced by 38.73%, 32.58%, 25.75%, and 13.6% compared to the VSR-LSTM, ATS-GRU, ASTGNN, and SP-LSTM, respectively.

Training time: It is an interval taken by the model to learn from the training data during the training phase.

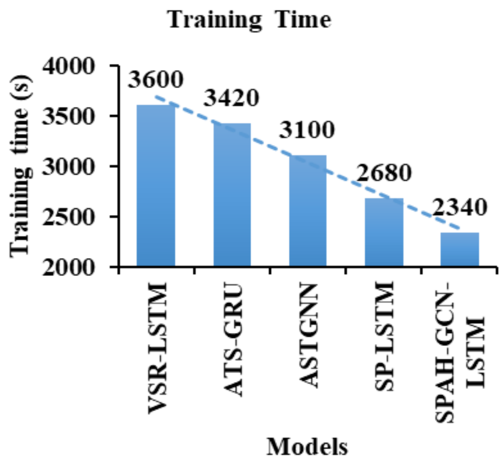

Figure 9 Comparison of Training Time for SPAH-GCN-LSTM with Existing Models

Figure 9 illustrates the training time for SPAH-GCN-LSTM compared to existing models. The results demonstrate that SPAH-GCN-LSTM surpasses other models in reducing training times. Specifically, the training time is decreased by 35%, 31.58%, 24.52%, and 12.69% compared to VSR-LSTM, ATS-GRU, ASTGNN, and SP-LSTM, respectively.

Prediction time: It is an interval needed to generate predictions on new, unseen data using the trained model.

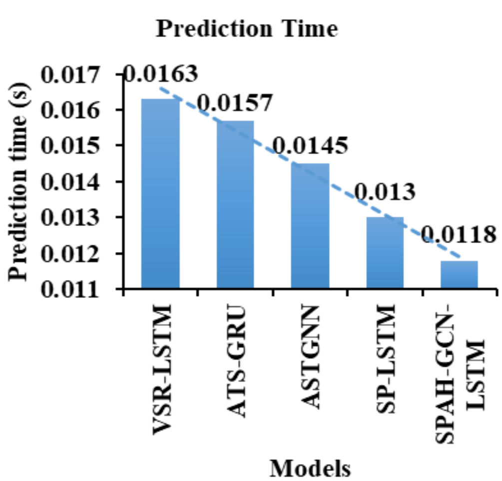

Figure 10 Comparison of Prediction Time for SPAH-GCN-LSTM with Existing Models

Figure 10 illustrates the prediction time for SPAH-GCN-LSTM compared to existing the prediction time is lowered by 27.61%, 24.84%, 18.62%, and 9.23% compared to VSR-LSTM, ATS-GRU, ASTGNN, and SP-LSTM, respectively.

4.4.1. Discussion

Accordingly, it can be concluded that the SPAH-GCN-LSTM model outperforms existing models in predicting network congestion for 6G networks. Its advanced design captures global and local spatial-temporal correlations in network traffic data, leading to greater accuracy and reduced error metrics. By incorporating global and local spatial-temporal modules with a soft attention strategy, this SPAH-GCN-LSTM model provides precise predictions of network congestion. The significant reductions in MAE, MSE, and RMSE indicate improved prediction capabilities crucial for proactive network management in 6G systems. The model's efficiency in training and prediction times makes it a promising tool for real-time network optimization and management in future 6G networks.

4.5. Performance Analysis for Network Route Optimization

Table 3 Network Links Ordered by Congestion Levels: Before and After Prediction

Order	Link_ID (Before Prediction)	Link_ID (After Prediction)
1	8	4
2	2	9
3	5	14
4	10	8
5	1	6
6	3	2
7	14	-
8	6	-
9	4	-
10	9	-

Analyzing the link order based on moving_mean_throughput before and after predictions (as illustrated in Table 3) can be used to improve network management. The reordering of links suggests potential network congestion issues, enabling proactive resource adjustments. In this context, a Q-Learning (QL) algorithm is utilized to identify optimal network paths based on predicted congestion conditions and real-time network data for data transfer. Thus, the efficiency of the QL

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algorithm is evaluated by considering factors such as average throughput, percentile rate across nodes, resource utilization, and computational overhead. A comparative analysis is conducted across various prediction models followed by QL for path optimization. Table 4 presents the average results of the QL model with different prediction models. Figure 11 to Figure 14 displays the performance of different models in optimizing network routes using outcomes of predicted models and real-time network data.

Table 4 Performance of Network Route Optimization After Congestion Prediction

Models	**Average** Throughput **(Kbps)**	**Percentile** Rate Across Nodes **(%)**	**Resource** Usage **(%)**	**Computation** Overhead **(ms)**
VSR-LSTM-QL	850	78	58	45
ATS-GRU-QL	890	82	52	41
ASTGNN-QL	940	85	47	35
SP-LSTM-QL	985	89	40	32
SPAH-GCN-LSTM-QL	1100	93	31	27

4.5.1. Average Throughput

- Average Throughput: It is the average amount of data (in bits or packets) successfully delivered to the destination per unit of time.

$$\text{Avg. throughput} = \frac{1}{N}\sum_{i=1}^{N}\frac{D_i}{t} \quad (20)$$

In equation (20), N is the number of successful data transmissions, D_i is the amount of data delivered in the i^{th} transmission, and t is the time.

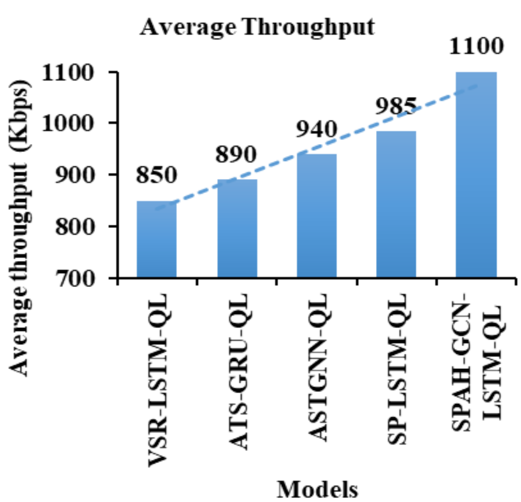

Figure 11 Comparison of Average Throughput

Figure 11 illustrates the Average throughput results for various route optimization models. The SPAH-GCN-LSTM-QL model outperforms others, increasing average throughput by 29.41%, 23.6%, 17.02%, and 11.68% compared to VSR-LSTM-QL, ATS-GRU-QL, ASTGNN-QL, and SP-LSTM-QL models, respectively.

- Computation Overhead: It refers to the extra processing time required by the RL model to compute routing decisions.

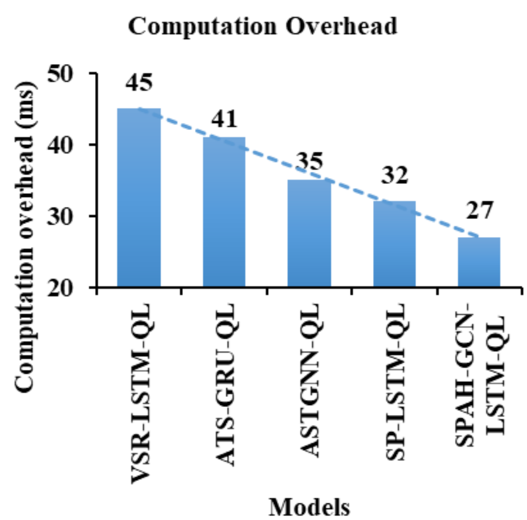

Figure 12 Comparison of Computation Overhead

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Figure 12 illustrates the Computation Overhead results for various route optimization models. Additionally, it reduces computation overhead by 40%, 34.15%, 22.86%, and 15.63% compared to VSR-LSTM-QL, ATS-GRU-QL, ASTGNN-QL, and SP-LSTM-QL, respectively.

- Percentile Throughput Rate Across all Nodes: It refers to the percentage of nodes in the network that achieve a certain performance threshold, such as throughput.

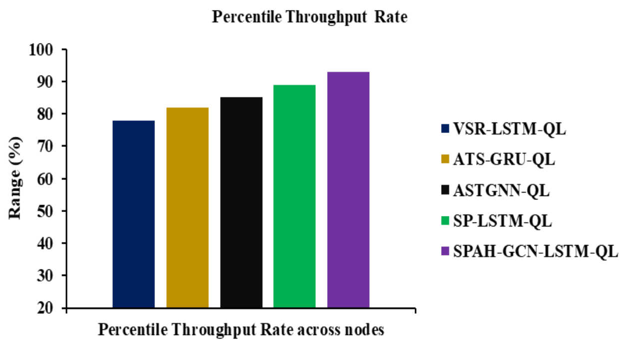

Figure 13 Comparison of Percentile Throughput Rate for Network Route Optimization

Figure 13 illustrates the percentile rate across nodes for various route optimization models. The SPAH-GCN-LSTM-QL model outperforms the VSR-LSTM-QL, ATS-GRU-QL, ASTGNN-QL, and SP-LSTM-QL models by increasing the percentile rate across nodes by 19.23%, 13.41%, 9.41%, and 4.49%, respectively.

- Resource Usage: It measures the amount of computational, memory, and bandwidth resources consumed by the RL model during the routing optimization process. The total resource usage is determined as follows:

$$R_{total} = R_{CPU} + R_{Memory} + R_{Bandwidth} \quad (21)$$

In equation (21),R_{CPU} is the CPU resources used, R_{Memory} is the memory consumed by the RL model, and $R_{Bandwidth}$ is the bandwidth used for communication between nodes.

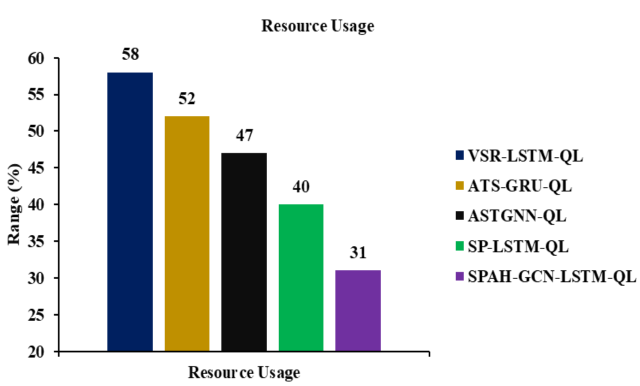

Figure 14 Comparison of Resource Usage

Figure 14 illustrates the resource usage results for various route optimization models. The SPAH-GCN-LSTM-QL model reduces resource usage by 46.55%, 40.38%, 34.04%, and 22.5% compared to the VSR-LSTM-QL, ATS-GRU-QL, ASTGNN-QL, and SP-LSTM-QL models, respectively. Accordingly, the SPAH-GCN-LSTM-QL model excels in throughput, congestion prediction, and routing optimization. It consistently delivers high performance across the network with the highest percentile rate. Its efficient design and accurate predictions result in minimal resource usage and low overhead for faster routing decisions.

5. CONCLUSION

This paper introduces a novel SPAH-GCN-LSTM model for predicting network congestion in 6G networks. This model combines global and local spatio-temporal correlations in network traffic flow data using two modules: global and local. Then, a soft attention strategy and softmax function are utilized to merge the outputs of these modules and predict network congestion probabilities. Moreover, the QL algorithm is applied to select the optimal route for data transfer based on the predicted congestion conditions and real-time feedback. Finally, experimental results proved that SPAH-GCN-LSTM-QL model achieves higher performance in network congestion prediction and route optimization compared to existing models in 6G networks. The SPAH-GCN-LSTM achieves a prediction accuracy of 0.9716, MAE of 0.095, MSE of 0.0141, RMSE of 0.1188, training time of 2340s, and prediction time of 0.0118s. Similarly, the SPAH-GCN-LSTM-QL achieves an average throughput of 1100Kbps, 93% percentile rate across nodes, 31% resource usage, and 27ms computation overhead compared to other models. Hence, this model serves as a valuable tool for network operators, facilitating efficient prediction of network congestion, fundamental for the management and optimization of future 6G networks.

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