Journal of Al-Qadisiyah for Computer Science and Mathematics Vol.17.(2) 2025,pp.Comp 146–152

Available online at www.qu.edu.iq/journalcm

JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS

ISSN:2521-3504(online) ISSN:2074-0204(print)

Incremental Deep Learning Application for Network Traffic Management

Samah Fakhri Aziz

University of al-Hamdaniya, Nineveh ,Mosul, Iraq. Email: samah.fakhri@uohamdaniya.edu.iq

ARTICLE INFO

Article history:
Received:14 /04/2025
Rrevised form: 07/05/2025
Accepted : 15 /05/2025
Available online: 30/06/2025

Keywords:
5G Networks
Deep Learning
Incremental Learning
Machine Learning
Network Slicing

ABSTRACT

One of the characteristics of 5G networks is their ability to create multiple virtual networks across a shared infrastructure, with resources dynamically allocated to meet the needs of different applications. However, managing these partitions in real-time remains a challenge due to their dynamic and heterogeneous nature. To overcome this challenge, this paper proposes an incremental learning model (ILM) that gradually learns from changing network data, seeking to improve the accuracy of partition selection. Unlike traditional models trained from static datasets, the ILM continuously updates its knowledge without the need to retrain from scratch. The results demonstrate the effectiveness of the proposed method, with an accuracy rate of 94.7%, while also demonstrating the ability to train using new traffic patterns and environments.

MSC..

https://doi.org/10.29304/jqcsm.2025.17.22190

1. Introduction

5G networks represent a transformation in wireless communication, providing high speeds, low latency, and the ability to accommodate a larger number of connected devices [1][2][3]. To achieve this, careful management of available resources is required [1][4]. One of the issues in 5G networks is the number of connected devices and applications that require varying quality types of service, therefore dynamic resource allocation is a need to achieve network performance [5][6]. Different requirements are demanded by applications. For example, applications such as remote surgery require very low latency (URLLC), while others such as 4K and 8K video streaming require high bandwidth (eMBB). Thus, network slicing techniques form a useful resource scheduling tool. Through these, multiple virtual networks can be created over the same physical infrastructure such that each of them is reserved for functioning with a specific type of application [7][8][9]10].

Despite the significant benefits that have been brought about by slicing approaches, dynamic resource allocation is faced with various challenges. One of them is adapting to dynamic requests and network changes, thereby future demands are difficult to forecast. Another one is maintaining operational and network costs, especially with resource-hungry applications [11][12]. On the other hand, network flexibility is an important aspect to ensure

∗Corresponding author: Samah Fakhri Aziz

Email addresses: *samah.fakhri@uohamdaniya.edu.iq*

Communicated by ‘sub etitor’

extended high performance, as the network needs to accommodate changing loads by adapting quickly. To overcome these challenges and provide the appropriate slices for each application, researchers have proposed using machine learning techniques to classify traffic and make appropriate slice decisions [13][14][15][16]. Others have proposed using deep learning algorithms to optimize resource allocation. Such algorithms, such as deep reinforcement learning, have shown the ability to find a compromise between latency and bandwidth while ensuring maximum resource utilization [17][18][19]. However, such algorithms face computationally intensive obligations with long training times. Other works have trained predictive models using neural networks to predict the future state of the network based on historical data with the aim of detecting future patterns and demands, thus improving the efficiency of resource allocation. However, these models depend on the quality of historical data. In some cases, this may affect their accuracy and performance. In this paper, the use of incremental learning is proposed to optimize resource allocation within 5G networks. The goal of the model is to find an architecture that adapts to sudden changes in the network as well as the time requirements of users. Finally, the performance of different deep learning models including SimpleNN, Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN) is further evaluated for comparison.

2. Related Works

A number of intelligent techniques for resource allocation in a 5G context using machine learning, deep learning, and deep reinforcement learning have been proposed. In [23], the authors proposed a multilayer network-slicing and resource allocation model for SDN and 5G networks based on NFV. Results indicated that such integration with machine learning models enhanced the network's scalability, resilience, and real-time adaptability, thus qualifying it to manage heterogeneous applications in 5G. In [25], a machine-learning approach was proposed to model 5G network slicing, with a focus on the design of an intelligent controller that can allocate network slices based on predicting traffic. Using supervised learning algorithms, they design an optimized slice allocation for various applications, thus ensuring improved bandwidth management and service quality in high-demand scenarios. In [22], the authors proposed machine learning algorithms as a way to monitor traffic in dynamic network slicing and allow real-time, on-demand variation in resource allocation. Predictive analytics results showed that several machine learning models could achieve better efficiency of the networks while decreasing congestion due to high bandwidth utilization. In [24], the authors made use of DRL in a relationship-based resource allocation strategy, where user-device relationships were harnessed to drive allocation decisions. Whereby DRL-based resource allocation provided a much better efficiency of the network under a dynamic environment, reducing handoff failures while ensuring seamless connectivity, compared to the traditional reinforcement learning algorithms. In [26], another inter-slice resource management model for 5G-RAN based on the markov decision process was used in order to balance the resource allocation across multiple slices. The results showed MDP-based optimization outperforms static allocation, especially with variable traffic loads. In [21], the authors presented a GCN and LSTM model-based resource allocation scheme for 5G networks. In doing so, this study tackled the intricate task of sufficiently capturing the inherent spatial and temporal dependencies of network traffic, which is an important feature for effective resource allocation. Where GCN focused on mining spatial correlations of the network nodes, LSTM was employed to model long-term temporal variations in traffic demand. Results showed higher predictive accuracy of resource and decreased latency. DRL-based techniques to optimize a resource in massive MIMO environments were studied in [27] and [28]. The results of their study revealed that DRL can effectively manage large-scale network deployments, increase spectral efficiency, and reduce interference in multi-tenant 5G networks. Still, the difficulties of training the DRL models were raised in both studies, thus the importance of efficient learning strategies for complexity reduction and real-time adjustment. In references [29] and [30] AI-based automation of network slicing and fault recovery in 5G networks are studied. Their studies reported the advantages of using machine learning in predicting potential network failures, allowing resource allocation to be adjusted to prevent service outages. By incorporating anomaly detection algorithms, their frameworks increased network resilience and reduced downtime. These works assume an increasing role of AI-based models with respect to resource allocation optimization and network slicing in 5G networks. While these techniques offer considerable advancements in network efficiency, scalability, and automation, challenges such as computational complexity, real-time adaptability, and model interpretability remain under-explored.

3. Proposed Method and Experiments

In 5G networks, a new model proposed an Incremental Learning Model (ILM) to classify segments of network traffic. The new model dealt with scalability, sustainable modeling, and reasonable classification accuracy apart from being able to adapt to continuous change in the network without complete retraining. It is based on an Adaptive Attention Mechanism. which allow resource allocation improvement and increased prediction accuracy by learning hidden layer relationships dynamically (See Figure 1).

In the proposed multi-layer deep neural network model, shallow networks are firstly trained to extract main features and then deep representations are utilized to further ensure prediction accuracy. Thus, predictive power of the model may be increased and computational complexity decreased in comparison with traditional methods. The proposed model consists of the ILM of hidden layers where each layer is assigned a different level of abstraction and incremental learning. y on the final output, the model relies on adaptiveUnlike traditional networks that rely onl attention-based pooling which distributes weights across all hidden layers to extract more complex features , from the data. The prediction function can be represented as follows:

$$f(x) = \sum_{l=1}^{L} \alpha_l f_l(x) \qquad (1)$$

W here $f_l(x)$Represents Classifier Document to Features Layer Hidden l. It$\alpha_l$is the attention weight, learned by a shallow neural network that calculates the relative importance of each layer.

It is done to update weights are added during the learning process to ensure that performance is gradually improved. This is done using an enhanced backpropagation algorithm, where the computational error is distributed across all hidden layers instead of just the last layer, enhancing the model's ability to gradually adapt to new data. The weights are updated according to the following equation:

$$W_{t+1}^{l} = W_t^{l} - \eta \nabla_{W^l} L_t \qquad (2)$$

Where W_t^l the weight Layer $l$in Time. and represents $t$an ηaverage Learning. And L_tIt is the error rate calculated during training.

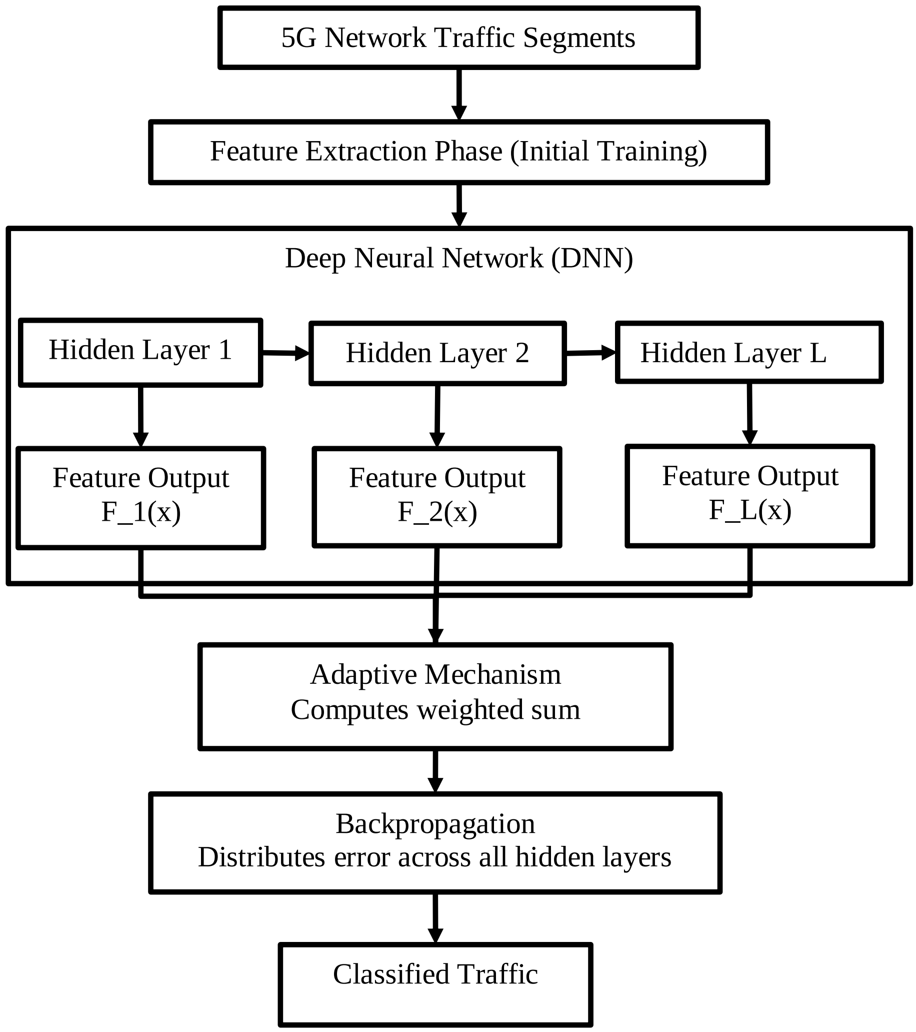

Figure (1): Architecture of Incremental Learning Model (ILM)

3.1. Dataset

To analyze the effectiveness of the proposed ILM model in dynamic resource allocation in 5G networks, the CRAWDAD dataset [31], which covers LTE and 5G technologies, across a range of use cases, was used. The dataset consists of a number of input and output features. These input features include the type of use case or application, LTE/5G user equipment classes, supported cellular technologies, days of the week, data collection times, and the distinction between guaranteed and non-guaranteed bit rate services. Moreover, the dataset captures metrics for assessing network reliability, such as packet loss rate, as well as latency metrics, in particular packet delay budget, which defines acceptable latency thresholds in milliseconds. The output feature indicates the type of network slice corresponding to each use case, with categories including enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC), and massive machine-type communications (mMTC). This dataset demonstrates its value in evaluating and optimizing cellular network performance, especially in the context of diverse use cases and their QoS requirements. The data was split into 80% for training and 20% for testing, where data processing operations were applied to ensure consistency of the inputs, including normalization.

3.2. *Preparing the proposed model*

The model was implemented using machine learning libraries such asTensorFlow and PyTorch and the training configurations. The variables were defined as in table 1.

Table 1 - Training configurations.

Parameters	Value	Description
Number of training epochs	50	Number of complete iterations on the training data
Batch Size	64	The number of samples passed to the model in each training cycle
LearningRate	0.001	It is automatically adjusted using AdaptiveLearning Rate (ALR) technology
Loss Function	Cross-Entropy Loss	Used to evaluate the performance of the model during training

The performance of the model was compared with several algorithms used in resource allocation within5G networks Traditional neural networks ,(SimpleNN) convolutional neural networks ,(CNN) recurrent neural and , networks(RNN) average batch , final accuracy :a number of criteria The model was evaluated based on accuracy training time and , average loss ,(seconds).

4. Results

The performance of the proposed (ILM) was evaluated and compared with several algorithms, including traditional neural networks (SimpleNN), convolutional neural networks (CNN), and recurrent neural networks (RNN). Table 2 compares the models for performance across batches, final accuracy, average batch accuracy, average loss, and training time (in seconds).

Table 2. Comparison of Model Performance Across Training Batches.

The model	Final accuracy %	Average batch accuracy%	Average loss	Training time(sec)
IncrementalNN	94.7	94.4	0.056	12.34
SimpleNN	91.5	91.0	0.089	9.56
CNN	89.4	88.9	0.102	15.67
RNN	87.6	87.0	0.110	14.23

As shown in table 2 Incremental achieves the highest accuracy across epochs. Theaccuracy evolution of each model was analyzed over fivetraining batch. TheFigure 2 shows the accuracy comparison between the four models.

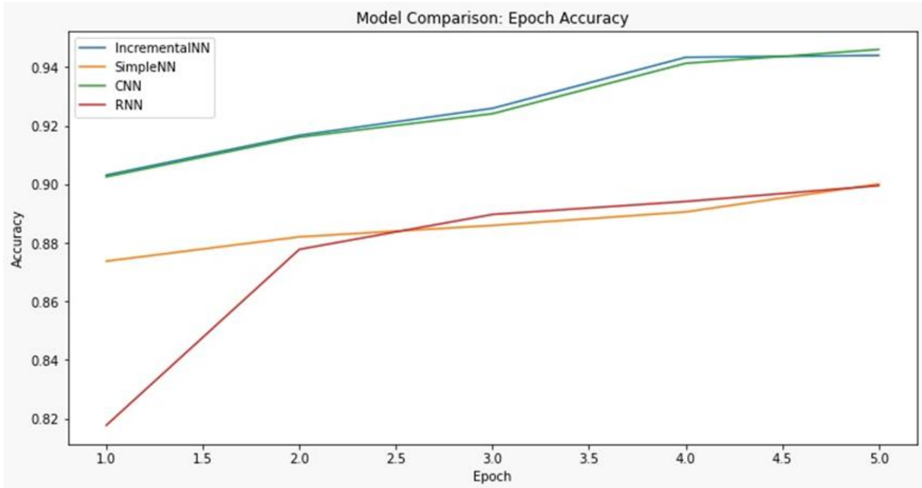

Figure (2): Accuracy comparison between models over five training batch.

Figure 2 illustrates the accuracy and stability of the model performance. The IncrementalNN and CNN models show stable accuracy gains across epochs, starting at over 90% in epoch 1 and gradually improving to around 94.7% at epoch 50. SimpleNN shows a slower, gradual improvement, starting at 87.5% and only reaching just under 89.5%. RNN, since it starts with a lower accuracy (around 81.8%), progresses rapidly in earlier epochs but remains below 90%.

5. Discussion

An ILM was designed to improve dynamic resource allocation in 5G networks. The proposed model's performance was experimented and compared with current models such as SimpleNN, CNN, and RNN, and the The proposed model demonstrated superior accuracy compared to baseline methods , efficiency, and adaptability with respect to changing networks dynamically. The ILM model achieved the highest final accuracy (94.7%) among current models. The proposed model was also distinguished by its ability to dynamically reconfigure to adapt to changes in the network without the requirement of complete retraining, hence reducing computational expense and improving performance in dynamic scenarios. Though Slightly More than for SimpleNN, Training Time for the ILM Model Was Lesser than for CNN and RNN with Higher Accuracy. The proposed model achieved the most reduced average loss of 0.056, demonstrating that it can more accurately predict and mitigate errors during resource allocation. However, though the proposed model has shown extremely positive results, the computational burden involved for incremental learning is a limiting factor for large and complicated networks. The quality of data available is very critical for training the model, representing high-quality and representative network data streams. Despite the potential of the proposed model, further tuning is required to meet the requirements of various 5G applications, such as URLLC, eMBB, and mMTC. Further research is also needed to reduce the computational complexity of the model using pruning or quantization on neural networks. Additional reinforcement learning methodologies could be applied to the proposed model to make it more dynamic and adapt to network modifications. More accurate representative data collection techniques could also be designed to improve model performance in heterogeneous network environments.

Conclusions

This paper proposes an Information Lifecycle Management (ILM) model to improve dynamic resource allocation in 5G networks. Comparative evaluation and analysis of performance metrics indicate that the proposed model performed better in terms of complexity, accuracy, and responsiveness to dynamic network changes. The proposed model achieved remarkable success in terms of resource allocation accuracy, making it an ideal candidate for improving network performance. Furthermore, the model can learn from dynamic and constantly changing networks without the need for a full retraining process, saving computational resources and improving performance in dynamic environments. Despite achieving the desired performance, there are still major drawbacks worth noting, such as the computational cost of training the model and the sensitivity of its output to the quality of the input data. These challenges can be addressed with improved algorithms and high-quality data collection techniques. Future research could improve this research model by incorporating reinforcement learning techniques for greater flexibility, or using compression and segmentation schemes to reduce computational complexity. The proposed model could serve as an intelligent controller at the network edge for real-time traffic analysis and resource allocation decisions. The proposed model can be integrated with existing network management systems (SDN/NFV) using APIs or deployed at the edges as a controller to make resource allocation decisions.

References

[1] S. Zeb, A. Mahmood, S. A. Hassan, Md. J. Piran, M. Gidlund, and M. Guizani, “Industrial digital twins at the nexus of NextG wireless networks and computational intelligence: A survey,” Journal of Network and Computer Applications, vol. 200, p. 103309, Jan. 2022, doi: 10.1016/j.jnca.2021.103309.

[2] P. Kumar and N. Sumit, “Review Paper on Development of Mobile Wireless Technology,” Journal of Physics Conference Series, vol. 1979, no. 1, p. 012024, Aug. 2021, doi: 10.1088/1742-6596/1979/1/012024.

[3] S. Sharma, M. Deivakani, K. S. Reddy, A. K. Gnanasekar, and G. Aparna, “Key enabling technologies of 5G wireless mobile communication,” Journal of Physics Conference Series, vol. 1817, no. 1, p. 012003, Mar. 2021, doi: 10.1088/1742-6596/1817/1/012003.

[4] M. A. Kamal, H. W. Raza, M. Alam, M. Alam, M. M. Su’ud, and A. Bakar Sajak, “Resource Allocation Schemes for 5G Network: A Systematic Review,” Sensors, vol. 21, no. 19, p. 6588, Oct. 2021, doi: 10.3390/S21196588.

[5] I. Al-Surmi, A. M. Mansoor, and A. A. Ahmed, “Toward 5G High Utilizations: A survey on OFDMA-based Resource Allocation Techniques in Next-Generation Broadband Wireless Access Networks,” vol. 6, no. 18, p. 168713, Feb. 2021, doi: 10.4108/EAI.10-2-2021.168713.

[6] W. Ejaz, S. K. Sharma, S. Saadat, M. Naeem, A. Anpalagan, and N. A. Chughtai, “A comprehensive survey on resource allocation for CRAN in 5G and beyond networks,” Journal of Network and Computer Applications, vol. 160, p. 102638, Jun. 2020, doi: 10.1016/J.JNCA.2020.102638.

[7] “5G Communication Systems: Network Slicing and Virtual Private Network Architecture,” ITM web of conferences, vol. 54, p. 02001, Jan. 2023, doi: 10.1051/itmconf/20235402001.

[8] P. Subedi, A. Alsadoon, P. W. C. Prasad, S. Rehman, N. Giweli, M. Imran, and S. Arif, "Network slicing: A next generation 5G perspective," EURASIP Journal on Wireless Communications and Networking, vol. 2021, no. 1, pp. 1–xx, Jun. 2021, doi: 10.1186/s13638-021-01983-7.

[9] F. Song, J. Li, C. Ma, Y. Zhang, L. Shi and D. N. K. Jayakody, "Dynamic Virtual Resource Allocation for 5G and Beyond Network Slicing," in IEEE Open Journal of Vehicular Technology, vol. 1, pp. 215-226, 2020, doi: 10.1109/OJVT.2020.2990072

[10] B. Han and H. D. Schotten, "Machine Learning for Network Slicing Resource Management: A Comprehensive Survey," ZTE Communications, vol. 68, no. 4, 2020. [Online]. Available: arXiv:2001.07974 [cs.NI]. doi: 10.48550/arXiv.2001.07974.

[11] M. Fahim and N. Elshennawy, "Efficient Resource Allocation of Latency Aware Slices for 5G Networks," Journal of Engineering Research, vol. 7, Jan. 27, 2023. doi: 10.21608/erjeng.2023.182438.1132.

[12] E. A. Mazied, L. Liu, and S. F. Midkiff, "Towards Intelligent RAN Slicing for B5G: Opportunities and Challenges," arXiv preprint arXiv:2103.00227, Feb. 27, 2021. [Online]. Available: https://doi.org/10.48550/arXiv.2103.00227.

[13] H. O. Otieno, B. Malila, and J. Mwangama, "Deployment and Management of Intelligent End-to-End Network Slicing in 5G and Beyond 5G Networks—A Systematic Review," IEEE Access, vol. 12, pp. xx–xx, 2024.

[14] M. Malkoc and H. A. Kholidy, "5G Network Slicing: Analysis of Multiple Machine Learning Classifiers," arXiv preprint arXiv:2310.01747, Oct. 3, 2023. [Online]. Available: https://doi.org/10.48550/arXiv.2310.01747.

[15] F. Xie, D. Wei, and Z. Wang, "Traffic Analysis for 5G Network Slice Based on Machine Learning," EURASIP Journal on Wireless Communications and Networking, vol. 2021, no. 1, 2021. [Online]. Available: https://doi.org/10.1186/s13638-021-01983-7.

[16] L. A. Garrido, A. Dalgkitsis, K. Ramantas, A. Ksentini, and C. Verikoukis, "Resource Demand Prediction for Network Slices in 5G Using ML Enhanced With Network Models," IEEE Transactions on Vehicular Technology, vol. 73, no. 8, pp. 11848–11861, Aug. 2024. doi: 10.1109/TVT.2024.3373490.

[17] J. Stigenberg, V. Saxena, S. Tayamon, and E. Ghadimi, "QoS-Aware Scheduling in New Radio Using Deep Reinforcement Learning," arXiv preprint arXiv:2107.06570, Jul. 14, 2021. [Online]. Available: https://doi.org/10.48550/arXiv.2107.06570.

[18] J. Jiang, Y. Qiu, Y. Su, and J. Zhou, "Low-Latency Resource Elements Scheduling Based on Deep Reinforcement Learning Model for UAV Video in 5G Network," Journal of Physics: Conference Series, vol. 1827, no. 1, p. 012071, Jan. 2021. doi: 10.1088/1742-6596/1827/1/012071.

[19] M. Alsenwi, N. H. Tran, M. Bennis, S. R. Pandey, A. K. Bairagi, and C. S. Hong, "Intelligent Resource Slicing for eMBB and URLLC Coexistence in 5G and Beyond: A Deep Reinforcement Learning Based Approach," IEEE Transactions on Wireless Communications, vol. 20, no. 7, pp. 4585–4600, Jul. 2021. doi: 10.1109/TWC.2021.3060514.

[20] N. Salhab, R. Langar, and R. Rahim, "5G Network Slices Resource Orchestration Using Machine Learning Techniques," Computer Networks, vol. 188, p. 107829, Apr. 7, 2021. doi: 10.1016/j.comnet.2021.107829.

[21] AR Alkhafaji and FS Al-Turaihi, “Multi-layer network slicing and resource allocation scheme for traffic-aware QoS ensured SDN/NFV-5G network,” in 2021 1st Babylon International Conference on Information Technology and Science (BICITS), pp. 327-331, April. 2021.

[22] N. Salhab, R. Langar, and R. Rahim, “5G network slices resource orchestration using machine learning techniques,” Computer Networks, vol. 188, p. 107829, 2021.

[23] A. A. Abdellatif, A. Mohamed, A. Erbad, and M. Guizani, “Dynamic network slicing and resource allocation for 5G-and-beyond networks,” in 2022 IEEE Wireless Communications and Networking Conference (WCNC), pp. 262-267, April. 2022.

[24] N. He, S. Yang, F. Li, and X. Chen, “Intimacy-based resource allocation for network slicing in 5G via deep reinforcement learning,” IEEE Network, vol. 35, no. 6, pp. 111-118, 2022.

[25] T. Mumtaz, S. Muhammad, M. I. Aslam, and I. Ahmed, “Inter-slice resource management for 5G radio access network using Markov decision process,” Telecommunication Systems, vol. 79, no. 4, pp. 541-557, 2022.

[26] X. Gao, J. Wang, and M. Zhou, “The research of resource allocation method based on GCN-LSTM in 5G network,” IEEE Communications Letters, vol. 27, no. 3, pp. 926-930, 2022.

[27] D. Yan, B. K. Ng, W. Ke, and CT Lam, “Deep reinforcement learning based resource allocation for network slicing with massive MIMO,” IEEE Access, vol. 11, pp. 75899-75911, 2023.

[28] Y. Xie et al., “Resource allocation for network slicing in dynamic multi-tenant networks: A deep reinforcement learning approach,” Computer Communications, vol. 195, pp. 476-487, 2022.

[29] R. Singh et al., “Analysis of network slicing for management of 5G networks using machine learning techniques,” Wireless Communications and Mobile Computing, vol. 2022, p. 9169568, 2022.

[30] A. A. Abdellatif et al., “Intelligent-slicing: An AI-assisted network slicing framework for 5G-and-beyond networks,” IEEE Transactions on Network and Service Management, vol. 20, no. 2, pp. 1024-1039, 2023.

[31] Anurag Thantharate, Cory Beard, Rahul Paropkari, Vijay Walunj, "CRAWDAD umkc/networkslicing5g", IEEE Dataport, December 8, 2022, doi:10.15783/k0w0-js18.