Migration Letters

Volume: 21, No: S5 (2024), pp. 1921-1926

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

Base Station Allocation For 6G Wireless Networks Using Wide Neural Network

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ABSTRACT

Terahertz (THz) transmission is a prominent technology in 6G mobile networks due to its enormous bandwidth and data transfer at fast speeds. in 6G wireless networks is crucial to managing massively increasing data rates and device connection for maximum performance and user experience optimum resource allocation is needed. It also allows dynamic network resource distribution for 6G's high device density and variable service requirements. Wide neural networks (WNN) can smooth network performance to address this issue. Paper proposes a WNN-based dynamic base station allocation method for 6G wireless networks. Training the WNN model with 14 6G parameters. Results show that the WNN strategy for dynamic decision-making in 6G networks works and might be used to other domains with comparable issues. With fewer fully connected layers, the wide neural network model performs better. Received validation accuracy is Interestingly, linear models without an activation function (None) perform as well as Tanh for single and two-layer topologies, with accuracy of 93% and 92%, respectively, and AUCs of 0.99. With three layers, accuracy decreases to 86%, still good.

Key Words: *6G wireless networks, Resource Allocation, Deep Learning, Wide Neural Networks, Activation Functions.*

INTRODUCTION

With its wide and complex needs, 6G is projected to enable the unprecedented Internet of Everything scenarios. To successfully meet numerous objectives, 6G envisions interconnected three-dimensional networks with various slices, utilizing new technologies and paradigms for increased intelligence[1] and flexibility. Complex, varied, and dynamic 6G networks make effective resource utilization, seamless user experience, and autonomous administration and orchestration problematic. As big data processing technologies, computing power, and rich data increase, AI may be used to address complicated 6G network challenges. Optimizing resource allocation is crucial for 6G-enabled IoT network performance.

The majority of current research focuses on massive data transfer for static jobs [1]. The 6G network, the newest mobile communication technology, enables large-scale dynamic networks [2]. The paper proposes a simple method for network nodes to determine base station status. A Wide Neural Network uses 14 6G parameters and dynamically allocates base stations. Figure1. Shows the 6G network scenario, where resources can be allocated as per users request using deep learning approach.

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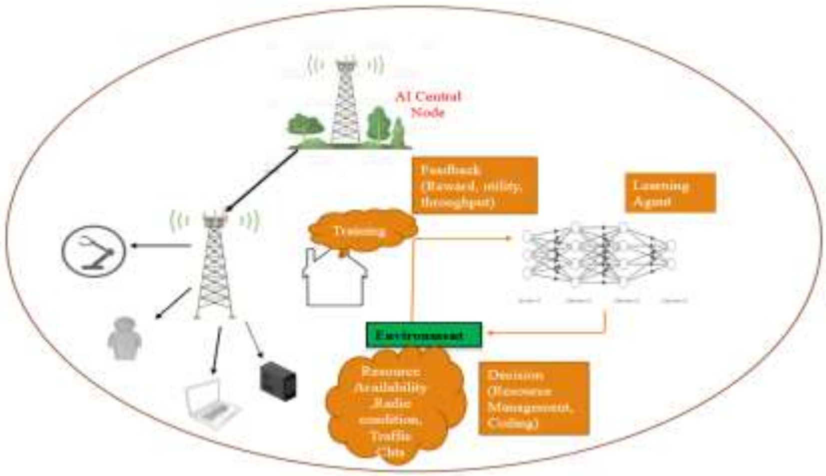


Figure 1. 6G wireless networks scenario

Wide neural networks categorize data [3]. This approach requires a labeled dataset for model training [6]. Neuron layers comprehend neural network input-output relationships. Each wide neural network layer in the proposed study comprises 14 neurons. For 100 users, wide neural networks are more effective. Iterating input data and modifying neural weights based on predicted and actual outputs trains the model. For accurate categorization, wide neural networks decrease error. Network monitoring and base station node notification occur during training. After training, the network applies the same input parameters to the new node to output. Nodes are tested for base station status. The intelligent base station allocation decision involves 14 inputs. For an educated conclusion, the network gets various input parameters during training. The 6G network adjusts to training. Based on binary judgments, WNN determines base station status. The judgment uses 14 input parameters and network training. Trial parameters determine base station allocation by the network. For 100 users on MATLAB classification learner, the suggested method calculates interestingly, for linear models without an activation function (None) perform as well as Tanh for single and two fully connected layer architectures, with accuracy of 93% and 92%, respectively, and area under the curve (AUC)s of 0.99. With three fully connected layers, accuracy decreases to 86%, which is still good compared to ReLU and Sigmoid. This was done by tuning model hyperparameters. The WNN's dynamic base station allocation and 6G parameter analysis are shown. ‘

LITERATURE SURVEY

Yang, Z. et al. shows A UAV-, NOMA-, and MEC-based AI system improves mobile task offloading and resource allocation to enhance connection, latency, and energy utilization. It examines federated learning and reinforcement learning to meet these obstacles, including their benefits and research issues [3]. Alsharif, M.H et al. finds that the paper synthesizes previous research to outline 6G wireless communication's envisioned characteristics, difficulties with possible solutions, and current research efforts, laying the groundwork for future research [4]. De Alwis et al. surveys AI-enabled 6G communication technologies and discusses how AI may improve localization, UAVs, and security, using a use case in intelligent transport systems [5]. Jiang, W et al. discusses the impending 6G mobile communication system, its need, use cases, technological requirements, current research, and a roadmap for its development, as well as 5G and its possible supporting technologies and problems [6]. Mathew, A. et al. introduces an AI-driven architecture for 6G networks to improve data discovery, service provisioning, system adaptability, and resource management for advanced applications, as well as network optimization and future research directions [7]. Yu, M et al. paper proposes a THz-band scheduling and power allocation technique for 6G networks to simplify resource allocation and improve concurrent transmissions and reduce interference. Simulations suggest this method improves throughput by 12.5% to 60.7% over conventional methods [8]. Zhang, X et al. presents FBC-based resource allocation strategies for 6G THz band nano-networks to maximize effective capacity, ensure strict QoS for mURLLC with statistical delay and error-rate bounds, and address energy limitations with energy harvesting to target 1 Tbps data rates [9]. Nikooroo, M et al. proposes Optimizing user clustering, transmission power allocation, and UAV placement increases communication coverage by 67% to 270% without boosting propulsion power in UAV-based mobile networks [10]. Benfaid, A et al. shows innovative deep reinforcement learning system, AdaptSky, optimizes 3D UAV placement and NOMA power distribution in communication networks, exceeding standard approaches in data rate, fairness, and generalization [11]. Alajmi, A et al uses actor-critic deep reinforcement learning (ACDRL) to dynamically optimize power allocation in multi-cell NOMA networks, outperforming RL, DRL, and OMA approaches in long-term sum rate [12].

METHODOLOGY

This article utilizes 14 6G parameters as input, with a sample size of 100 random users. For the creation of a real-world simulation environment, 14 parameters are selected based on an extensive literature review to define the base station and users. The spacing between the Tera Hertz base station and nodes is set at 20 meters. Each node is connected to 10 partner nodes. The necessary factors for constructing the feature matrix for dynamic allocation of base stations are channel noise, bandwidth, delay, distance from base station, central frequency, packet length, number of packets, number of partner nodes, and load location. A neural network data set is created by implementing test considerations, forming a supervised data set for training a wide neural network. 80% of the input data metrics are allocated for training, while the remaining 20% is designated for validation. The results are kept in categorical format.

Effectiveness of dynamic base station allocation is determined through fine tuning the hyperparameters of a wide neural network. The number of fully connected layers utilized are one, two, and three, with each fully connected layer having a size of one hundred. The activation functions utilized include ReLU, sigmoid, tanh and none, with the exception of the final layer. Setting the iteration limit to 1000, the regularization strength Lambda is chosen as 0.1. After training the model, a meticulous tuning of hyperparameters is conducted to determine if the node will function as a base station.

RESULTS AND DISCUSSION

The study evaluated the performance of a wide neural network for base station allocation using a dataset of 100 users. The neural network was trained with various hyperparameters, such as fully connected layers and activation functions. The network's performance is assessed based on validation accuracy and area under the curve (AUC). Table 1. displays the tuning of hyperparameters for Wide Neural Networks.

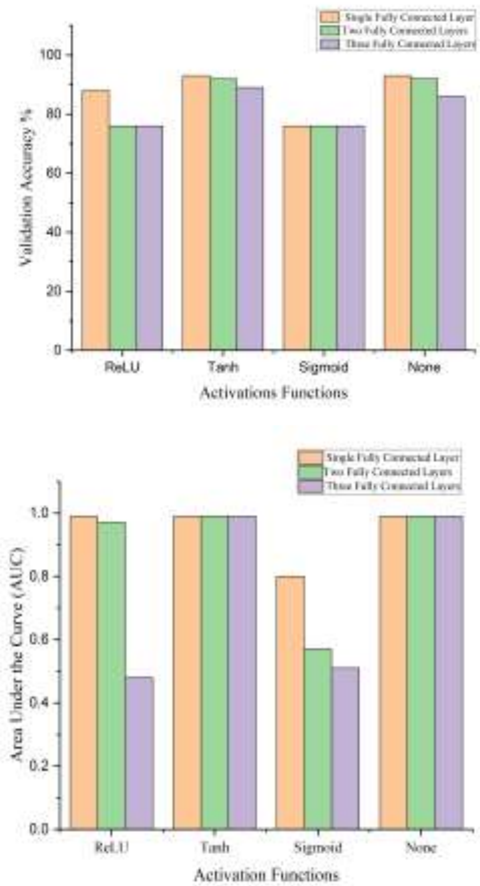
Table1. Tuning of hyper parameters for Wide Neural Networks

No of Fully connected layers	**First layer size**	**Second layer size**	**Third layer size**	**Iteration Limit**	**Regularization strength Lambda**	**Activation Function**	**Validation Accuracy%**	**AUC**

1	100	0	0	1000	0.1	ReLU	88	0.99
1	100	100	0	1000	0.1	Tanh	93	0.99
1	100	0	0	1000	0.1	Sigmoid	76	0.8
1	100	0	0	1000	0.1	None	93	0.99
2	100	100	0	1000	0.1	ReLU	76	0.97
2	100	100	0	1000	0.1	Tanh	92	0.99
2	100	100	0	1000	0.1	Sigmoid	76	0.57
2	100	100	0	1000	0.1	None	92	0.99
3	100	100	100	1000	0.1	ReLU	76	0.48
3	100	100	100	1000	0.1	Tanh	89	0.99
3	100	100	100	1000	0.1	Sigmoid	76	0.51
3	100	100	100	1000	0.1	None	86	0.99

Rectified linear unit (ReLU) activation function yield an accuracy rate of 88% with an AUC of 0.99, particularly in deeper neural network architectures. The accuracy drops to 76% with corresponding AUC values of 0.97 and 0.48.

When using the Tanh activation function, the accuracy achieved is 93% for a single fully connected layer network, 92% for two layers, and 89% for three layers. The AUC remains consistent at 0.99. When examining the performance of the sigmoid activation function in neural networks, it consistently achieved an accuracy of 76% across single, two, and three fully connected layers. The corresponding AUC values were 0.8, 0.57, and 0.51 for each configuration. The model without any additional features, essentially a linear model, performs comparably to the top-performing models for both single- and two-layer configurations, achieving an accuracy of 93% and 92% respectively. Having an AUC of 0.99 and an accuracy decrease to 86% with three layers, which is still relatively high. Figure 2.



(a) (b)

Figure 2. Performance measures for wide neural networks (a) Validation Accuracy Vs activation functions (b) Area under the curve Vs Activation Functions with single, two and three fully connected layers

The results in Figure 2(a) show the validation accuracy of a wide neural network model using different activation functions including ReLU, tanh, Sigmoid, and none (linear) across different numbers of fully connected layers. Results depicted in Figure 2(b) illustrate the area under the curve (AUC) for different activation functions including ReLU, tanh, Sigmoid, and none (linear) across different fully connected layers. A higher AUC value indicates superior model performance. The tanh activation function consistently demonstrates higher AUC values for different numbers of hidden layers compared to the sigmoid and no activation functions.

CONCLUSION

The wide neural network model is detailed, trained to make decisions based on fourteen input parameters of 6G network for each node, achieving accurate classification. The Tanh activation function demonstrates consistent performance across different fully connected layers in neural networks, achieving high AUC values. Interestingly, the linear model performs well when the problem is linearly separable. ReLU shows good performance in a single fully connected layer but struggles to maintain this performance as more fully connected layers are added. The sigmoid function is effective in terms of accuracy and AUC. Based on the specific setup, the tanh activation function demonstrates strong performance. The algorithm presented provides a practical solution for optimizing resource allocation and highlights the significant impact of deep learning algorithms on the advancement of 6G networks.

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