Indonesian Journal of Electrical Engineering and Computer Science
Vol. 34, No. 3, June 2024, pp. 1690~1697
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v34.i3.pp1690-1697

Dynamic base station allocation for 6G wireless networks through narrow neural network

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Article Info

Article history:

Received Dec 21, 2023
Revised Mar 5, 2024
Accepted Mar 16, 2024

Keywords:

6G wireless networks
Activation functions
Deep learning
Narrow neural networks
Neural networks
Resource allocation

ABSTRACT

The 6G wireless communication system will utilize the terahertz (THz) frequency band (0.1-10 THz) to meet customer demand for increased data rates and ultra-high-speed communication in future applications. The exponential surge in data traffic, which is supported by dynamic resource allocation. To mitigate this challenge, the use of artificial intelligence-based methods, such as narrow neural network (NNN), can help to smooth the performance of the network. In this paper, an NNN-based approach for dynamic base station allocation for 6G wireless networks is proposed 14 different 6G parameters used to train the NNN model, initially achieving an accuracy of 89.5% and an F1 score of 0.72 for 200 users. Results demonstrate the efficacy of the proposed NNN approach for dynamic decision-making in 6G networks and its potential for application in other domains where similar problems exist. Moreover, the proposed narrow neural network model shows improved results with an increase in number of users and decrease in fully connected layers and regularization strength (lambda). The validation accuracy received is 98.9% and 99.6% for thousand users with single fully connected layer, none (linear) activation function and regularization strength lambda values of 0.01 and 0.001.

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1. INTRODUCTION

The 6G communications vision improves data rate and latency and enables pervasive connectivity [1]. It is expected to connect terrestrial, aerial, and maritime communications into a powerful, faster, more reliable network [2]. The expansion of mobile technology has increased the need for efficient and dependable communications networks. The base station is a crucial communications network component [3]. Base stations connect mobile devices. Base stations handled thousands of users with high-powered signals [4]. This method was simple, but it increased base station power and decreased bandwidth and performance when mobile devices connected. With 5G and 6G networks, base station decentralization is necessary for efficient and reliable operation. Each home will have a pico or femto node connected to a high-speed backhaul optical fiber network when 5G is completely deployed. It makes sense to use home routers as transceivers to reduce power transmission.

The 6G network's increased broadcast frequency will lower transmission distances by one, requiring base stations to be close to consumers. Given these factors, dynamically assigning base stations, like mobile handoffs, makes sense. This dynamic base station placement optimizes network performance and reliability while decreasing transmission power. In the proposed work, describes a simple approach for network nodes to determine if they can be base stations. The method is to use a narrow neural network (NNN) to assess fourteen 6G parameters and allocate base stations dynamically. A narrow neural network classifies data into categories [5].

The supervised learning approach requires a labeled dataset for model training [6]. Neuron layers understand neural network input-output relationships. Each "narrow" neural network layer in the proposed study comprises 14 neurons. For 200 users, narrow neural network is faster and more effective. Iterating input data and modifying neural weights based on expected and actual outputs trains the model. For accurate categorization, narrow neural network reduce error.

Evaluation of literature dynamic base station allocation debuted in 1993 and dynamic allocation of frequencies was needed. Only reallocation of frequencies was discussed, while we treat the entire node as a base station or network user. Cousik *et al.* proposed 5G and 6G mm Wave networks, and deep IA, a deep learning-based solution, predicts optimum beams from few sweeps with over 100% accuracy [7]. Hadi *et al.* optimized HetNet uplink radio resource allocation for 6G stroke outpatients using Big Data Analytics-powered machine learning to signal to interference and noise ratio by 57 % and 95 % [8]. Gui *et al.* demonstrated a deep learning-enhanced non-orthogonal multiple access approach that improves system performance [9].

A deep neural network (DNN) is modeled, optimized, and trained to allocate power in distributed automation system by Qian *et al.* DNN optimize power schemes better than sub-gradient methods, enhancing spectrum and energy efficiency in communication systems [10]. Alfaia *et al.* recommend estimating network use with low power amplifier and ultra compact power amplifier. employing unmaned arial vechicle-base station to temporarily relieve mobile network congestion [11].

Lin *et al.* improves antenna selection and channel extrapolation in large multi input multi output systems with adaptive switching network and advanced dynamic network. It beats uniform selection and deep neural networks in channel, coherent channel mapping extrapolation, and beam prediction [12]. Using AI, Luo *et al.* improve mobile network with AI application to improve quality of service using Chinese telecom provider data [13]. Kumaresan *et al.* used artificial neural networks (ANN) to learn cluster formations using channel gains and transmitting power to boost non-orthogonal multiple access user clustering throughput for 5G user clustering [14]. Alwarafy *et al.* propose a deep reinforcement learning framework for multi-radio access technology assignment and dynamic power allocation in 6G networks with high heterogeneity for 6G [15].

The deep learning method by Dong *et al.* reduces base station power consumption and enhances quality of service (QoS) by allocating 5G radio resources using cascaded neural networks [16]. Sun *et al.* lightweight digital twin (DT) architecture for air-ground networks improves modeling efficiency and privacy through federated ground device learning and a distributed incentive mechanism [17]. Adeogun *et al.* proposed recurrent neural network (RNN) models for dynamic channel allocation in 6G networks and improve quality of service with 97.16% accuracy [18]. Ashwin *et al.* 6G hybrid quantum deep learning (HQDL) model improves QoS through resource management using CNN [19]. Alkhlefat *et al.* mentions 6G wireless technologies being developed to meet the high bandwidth and capacity needs of interactive applications like virtual reality and driverless vehicles [20].

Dynamic base station allocation, power and resource management using deep learning, machine learning, and deep reinforcement learning frameworks were developed by the main contributors to improve network performance and efficiency. Other methods that were optimized for 5G and 6G networks to increase energy efficiency, throughput, and quality of service were antenna selection, channel allocation, and user clustering. Leading researchers in the field have discovered that cutting-edge algorithms and deep learning techniques can optimize resource allocation, improve system throughput and QoS in 5G and 6G networks, and drastically decrease power consumption at base stations. This points to a promising future for mobile network technologies. With an emphasis on the necessity for better ways of dynamically evaluating and assigning base stations using narrow neural network for efficient operation and coverage, the manuscript tackles the unresolved issue of optimizing 6G network performance and reliability through dynamic base station allocation without increasing power consumption. Resulting in the improvement of validation accuracy of 23.39 % as compared to the existing work.

To optimize the performance and reliability of 6G networks while minimizing power consumption, we have developed and implemented a NNN model that dynamically allocates base stations based on real-time evaluation of fourteen distinct network parameters. This model is one of our new contributions. Conceptual 6G base station allocation is shown in Figure 1. The diagram explains how to choose a base station node. Gathering fourteen node input parameters begins the procedure. Parameters train NNN.

The network is monitored and notified of base station nodes during training. The network provides output by applying the identical input parameters to the new node after training. The network tests nodes for base station status. An intelligent base station allocation decision requires 14 inputs. The network receives many input parameters during training to make an informed decision. The 6G network learns and adapts through training. NNNs output binary decision on whether a node is a base station. The network allocates base stations based on input parameters during the trial phase. On MATLAB classification learner, the proposed technique had an F1 score of 0.72 and 89.5 % accuracy for 200 users, shows base station allocation and 6G parameter analysis capabilities.

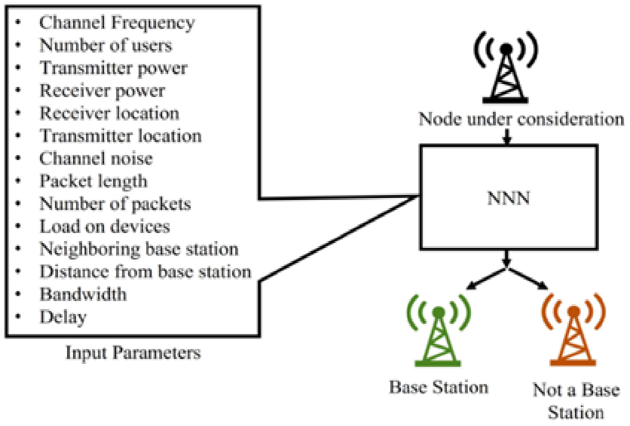


Figure 1. 6G base station allocation with network parameters

2. METHOD

The suggested work that is used in the paper is first fourteen 6G parameters are initialized. A total of 200 users were randomly selected and assigned to each base station. To simulate real-world conditions. the transmitted power was set at 30 dBm. To assure realism, a 6G frequency of 1 THZ was used as the primary carrier frequency, and each user was permitted a reception power range of -65 to -75 dBm. Each user’s position was determined using X and Y coordinates (Xc, Yc), with a specified range of 0 to 1,000 meters for 6G network base stations. Random channel noise between 0 and -0.5 dB was introduced to enhance the simulation’s realism.

Network formation simulates real-world traffic patterns using 32-byte packets and zero to 1,000 packets per transmitter. The study examined base station user capacity limits. Base stations could handle 20 users and 10 partner nodes per transmitter. Distance between the tera-hertzs (T)-base station and partner nodes was also considered, with a range of 0 to 20 meters [21]-[26].

The final feature matrix for dynamic base station allocation included parameters needed are Bandwidth, channel noise, delay, base station distance, center frequency, packet number, packet length, partner node, transmitted power, location, and load were these factors. Allocating base stations to more than 10 nearby users were required for the devices to become a base station. The previous base station must be 20 meters from the current device.

The implementation of these test conditions created a supervisory dataset for NNN training. The NNN was trained using 80% of the input data matrix as binary outcomes (Y train). The remaining 20% was validated and kept as categorical results. A confusion matrix was used to examine accuracy of 200 randomly selected samples for validation and testing. The accuracy, precision-recall, and F1 scores from this investigation were utilized to evaluate the deep learning-based dynamic base station allocation. The neural network model and hyperparameters are set as below:

Number of fully connected layers=1, 2, 3
Size of each fully connected layer=10, 20, 30, 40, 50, 60
Activation function for all layers except the final layer=ReLU, Sigmoid, Tanh and None
Iteration limit=1,000
Regularization strength (Lambda)=0.1, 0.2, 0.3
Standardize the numeric predictors.

Binary output decision is a y parameter, and the trained model classifies input parameters to determine base station allocation. Model hyperparameters were carefully tuned using classification learner. The number of fully connected layers and their sizes were given. For all layers except the final one, rectified linear unit (ReLU), Sigmoid, Tanh, and None were evaluated for activation. This study used a neural network model with 14 input parameters and a binary output decision representing base station allocation.

3. RESULTS AND DISCUSSION

NNN architecture evaluation results for 6G base station allocation are shown in Figure 2. The findings of the confusion matrix evaluation are reported as true positive (TP), true negative (TN), false positive (FP), and false negative (FN) values. The model was trained to predict base stations from 200 nodes.

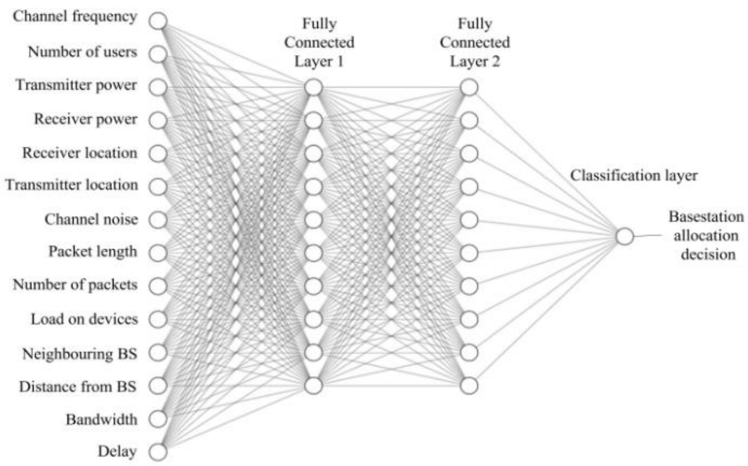
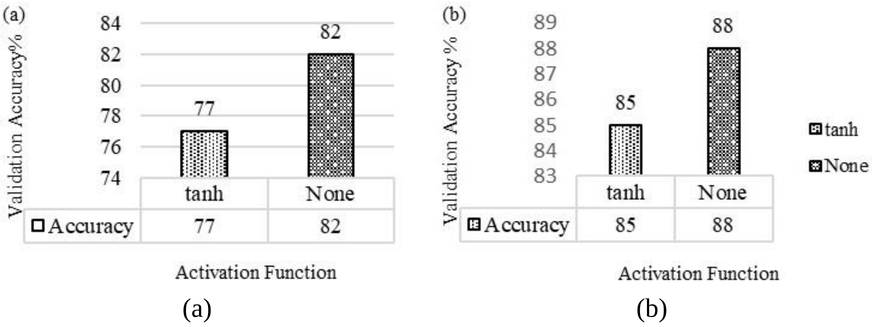


Figure 2. NNN architecture

The performance of a NNN for base station allocation has been evaluated with 200 users. Hyperparameters such fully connected layers, activation functions, regularization strength, and iterations were used to train the network. A single fully connected layer with 20 neurons, None activation function, 0.1 regularization strength, and 1,000 iterations performed best. This model achieved 89.5% validation accuracy, which was much higher than ReLU, Sigmoid, and tanh models.

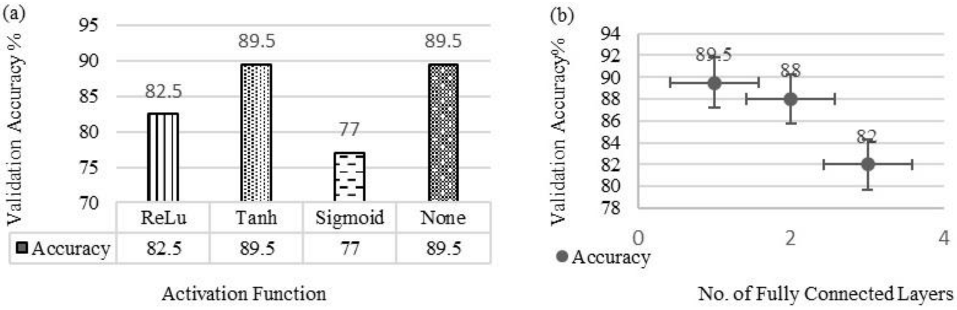
Figure 3 compares validation accuracy and activation function. Figure 3(a) demonstrates None activation function has 82% validation accuracy, greater than Tanh. The network has three fully connected layers, and Figure 3(b) indicates that None activation function has higher validation accuracy than ReLU, Sigmoid, Tanh, and None for two fully connected layers. The accuracy of None and Tanh is higher than ReLU and Sigmoid.



(a) (b)

Figure 3. Validation accuracy Vs activation function (a) with three fully connected layers for Tanh and None activation function and (b) with two fully connected layers for Tanh and None activation function

The relation between validation accuracy and activation function is shown in Figure 4. Figure 4(a) demonstrates that the validation accuracy improves to 89.5% when only single fully connected layer of 20 neurons is used. Figure 4(b) shows that the validation accuracy of the None activation function with single fully connected layer is 89.5%, which is higher than the validation accuracies of the None activation function with fully connected layers 2 and 3, which are 88% and 82%, respectively. NNN with one fully connected layer are used to determine additional performance indicators.



(a) (b)

Figure 4. Validation accuracy Vs activation functions and number of fully connected layers (a) validation accuracies for various activation functions and (b) gives the comparison of None activation function for 1, 2, 3 fully connected layers

Performance measurements for single fully connected layer neural network using ReLU, Sigmoid, Tanh, and None activation functions. For three, two, and one hidden layer, the NNN model has the maximum accuracy. This study compares Tanh and various activation functions to None, which offers 82%, 88%, and 89.5% validation accuracy. After explaining None activation function measuring parameters, 152 of 200 nodes were accurately categorized as non-base stations. However, the network misidentified 2 nodes as base stations, causing false positives. The network properly identified 27 of 46 base stations and misclassified 19 others. The network identified 58.70% of base stations with 0.5870 sensitivity. The network discovered 98.74% of non-base station nodes with specificity 0.9874. The network's positive predictions are accurate with 0.9310 precision. The F1 score was 0.72, indicating strong precision and recall. Equation 5 yielded 0.895 network accuracy. The graphical representation of the various measuring parameters based on confusion matrices for single fully connected layers with different activation functions, namely ReLU, Sigmoid, Tanh, and None are shown in Figure 5.

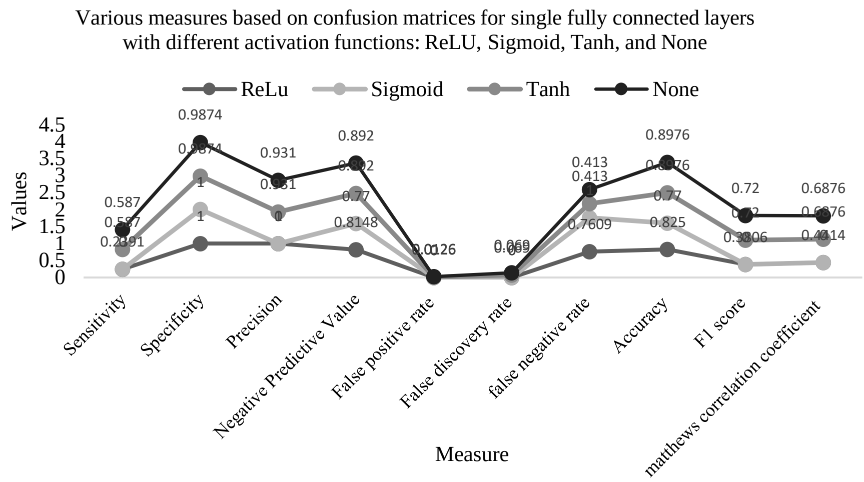


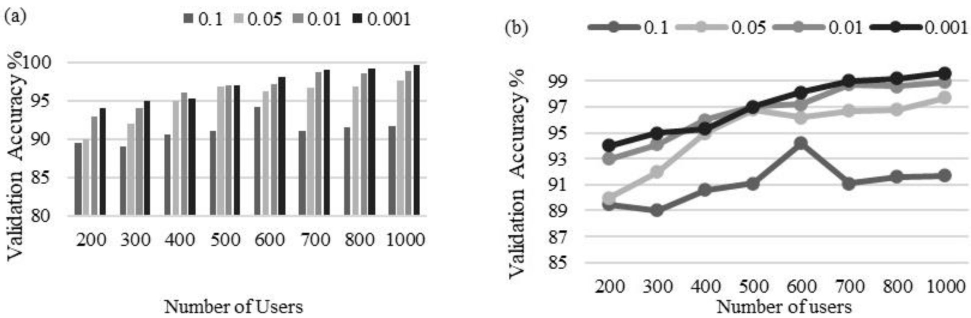
Figure 5. Various measures based on confusion matrices for single fully connected layers with different activation functions: ReLU, Sigmoid, Tanh, and None

In the previous section, 200 users' accuracy and measurement parameters were computed. A NNN with a single fully connected layer is validated using a None activation function and regularization strength lambda values of 0.1, 0.05, 0.01 and 0.001 for a dataset with 200, 300, 400, 500, 600, 700, 800, and 1,000 users. Validation accuracy improves as the number of users increases and lambda decreases. Table 1 shows 99.6% accuracy for 1,000 users with 0.001 regularization.

Table 1. Accuracy for NNN with single fully connected layer for None activation function or different Regularization strength value (lambda)

Neural network with single fully connected layer for None								
Regularization Strength (Lambda)	Number of users							
	200	300	400	500	600	700	800	1000
0.1	89.5	89	90.6	91.1	94.2	91.1	91.6	91.7
0.05	90	92	95	96.8	96.2	96.7	96.8	97.7
0.01	93	94.1	96	97	97.2	98.7	98.6	98.9
0.001	94	95	95.3	97	98.1	99	99.2	99.6

Figure 6 shows the relation between the validation accuracy and number of users. Bar graph and line graph of single fully connected layer with 20 neurons, 1,000 nodes, None activation function, regularization strength of 0.01 and iteration limit of 1,000 differentiation between base stations and non-base stations are shown in Figures 6(a) and 6(b) The NNN method may distinguish base stations from non-base stations. To boost sensitivity, future studies may examine further NNN design changes. For instance, more calculations are done.



(a) (b)

Figure 6. Effect of regularization strength (lambda) for 0.1, 0.05, 0.01, 0.001 on validation accuracy and number of users (a) relation between validation accuracy and number of users using a grouped bar graph and (b) relation between validation accuracy and number of users using a line graph

The research shows that the NNN methodology can facilitate dynamic decision-making in 6G networks, suggesting its use in similar circumstances. As the users increases, the NNN model performs better with fewer fully linked layers and lower regularization strength (lambda). This trend shows the model's capacity to scale and manage larger datasets without sacrificing efficiency or accuracy. The NNN technique is robust in complex, dynamic contexts and can be fine-tuned for best performance, according to findings. Table 2 gives the comparison of proposed work with existing work. Which show the various author's work.

Table. 2 Comparison of proposed work with existing work

Method	% Improvement	Validation accuracy %	Frequency GHz	Number of users equipments
Gui *et al*. [9]	0	76	-	32
Qian *et al*. [10]	7.6	92	-	-
Alfaia *et al*. [11]	14.65	85	0.02	2,000
Lin *et al*. [12]	8.6	91.04	28	-
Luo *et al*. [13]	4.84	95	28	-
Kumaresan *et al*. [14]	1.63	98	-	12
Alwarafy *et al*. [15]	2.57	97.1	6	-
Dong *et al*. [16]	10.66	90	0.00012	2,500
Sun *et al*. [17]	3.12	96.58	-	-
Adeogun *et al*. [18]	24.5	80	6	-
Ashwin *et al*. [19]	2.51	97.16	-	-
Proposed Method	23.39	99.6	1,000	2,000

Gui *et al.* [9] dosent show improvement with 76% accuracy. Alfaia *et al.* [11], showed enhanced validation accuracy of 85% and improvement of 14.65%. Whereas Qian *et al*. [10] improved by 7.6% showing 92% validation accuracy for 2,000 users. Lin *et al.* [12] noted an 8.6% gain with 91.04% validation accuracy at 28 GHz. Luo *et al.* [13] showed improvement of 4.84% at 28 GHz with validation accuracy of 95%. With 12 users, Kumaresan *et al.* improved 1.63% with 98% of validation accuracy. Alwarafy *et al.* [15] resulted in 97.1% validation accuracy with enhancemet of 2.57% at 6 GHz. Dong *et al.* [16] enhanced 10.66% and 90% validation accuracy at 120 KHz with 2,500 users. Sun *et al.* [17] increased accuracy by 3.12% which is 96.58%. Adeogun *et al.* [18] increased accuracy 24.5 at 6 GHz which is 80%. Ashwin *et al.* [19] improved 2.51% which is 97.16% validation accuracy. Finally, with 1 THz frequency, and 2,000 user devices, our method enhanced accuracy by 23.39% which is validation accuracy of 99.6%.

The results show how narrow neural network may be used to optimize dynamic base station allocation in 6G networks, emphasizing the significance of scalability and hyperparameter tuning for enhancing decision-making precision and network efficiency. Long short-term memory (LSTM) and other deep learning algorithms could be used to improve base station allocation in future studies. The NNN architecture may potentially improve base station identification by adding additional relevant data, such as node movement patterns and location. Future research should aim to improve 6G dynamic base station allocation methods. Future work can increase or decrease the amount of input characteristics used in decision-making for accuracy or speed. This research suggests that small neural network could be used for dynamic base station allocation in 6G networks, and that artificial intelligence could be crucial to their growth.

4. CONCLUSION

The study demonstrates the efficacy of NNN techniques in dynamically allocating 6G base stations. Utilizing 14 input parameters, the NNN model accurately classified stations and non-stations, achieving 89.5% accuracy and a 72% F1 score. While offering a viable solution for 6G network allocation challenges, the algorithm's performance can be enhanced through hyperparameter tuning. Validation results highlight the correlation between user count, regularization strength, and precision. This research lays the groundwork for further exploration of NNNs in 6G base station allocation, emphasizing their potential for optimizing resource allocation. It underscores the pivotal role of deep learning in shaping the evolution of advanced 6G networks.

ACKNOWLEDGEMENTS

The authors would like to thank the colleagues of Thadomal Shahani Engineering College for all their support.

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