Optimization of Base Station for 6G Wireless Networks for Efficient Resource Allocation using Deep Learning

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Abstract— **Sixth Generation (6G) networks are currently being investigated to cope with the increasing number of devices in the communication network. The parameters of 6G are still a work in progress but it is speculated that 6G will have a transmission speed of up to 100 Gbps with a frequency band that could be in terahertz. To contribute to the study on optimization of 6G networks we have developed a novel neural network called BSOnet that takes different parameters as input and then gives an output about the state of the base station in the network. With our proposed algorithm we were able to achieve a decreased power consumption in the network. We believe that study will pave the path for future studies on the optimization for 6G networks using deep learning.**

Keywords—*6G Wireless network, Deep learning, Neural network, resource allocation*

I. INTRODUCTION

Currently, Sixth Generation (6G) is under development wireless technology which is the successor of the currently used Fifth Generation (5G) cellular data network. It is expected that 6G will reach the data-rate of 100 Gbps with the frequency band used in terahertz [1]. The 6G will also be divided into geographical sectors like its predecessor. Each section will be known as a cell. Like 5G it is expected that 6G will also have multiple levels of base stations e.g., pico-net, Femto-net, macro-net, etc. Multiple companies like Huawei and Samsung have already started work on 6G and even China has launched the first 6G technology satellite for testing into the geostationary orbits [2]. These 6G satellites work at terahertz frequency and are generally paired in a group of 12 satellites.

It is expected that the 6G network will have support applications starting from current mobile cellular service, augmented and virtual reality, ubiquitous instant communication, internet of things, etc. It is expected that 6G will support all the technologies developed before it which means all the 5G handsets will work with 6G as well. Although the 6G works in the terahertz range the size of the antenna will be measurable using a reflective intelligent surface [3]. The 6G network will work on a spectrum sharing basis and will involve mobile edge computing, artificial intelligence, modern security tools such as blockchain, and smaller packets for communication. Gallium nitride High Electron Mobility Transistor (HEMT) with n-type doping that will allow manufacturing of 6G transponder because of its ability to work with extremely high frequencies. Japan has already created terahertz ships, which will be mandatory for 6G technology. The maximum speed achieved in the initial 6G network is 206.25 Gbps.

Artificial Intelligence (AI) is an emerging technology that allows optimization for 6G network parameters such as architecture, protocol, and data transfer operations. 6G will be a human-centric network with key benefits of secrecy and privacy and still will be able to support all the traditional 5G mobile applications. Currently, in the discussion, 95 GHz to 3 THz frequency and F, D, G, and Y bands are licensed for the 6G spectrum along with all the existing 5G bands for back compatibility [4].

In this paper, we have simulated a basic 6G network. Optimization for one parameter, namely the number of required base stations has been done with a deep-neural network technique called Base-Station-Optimizer-net (BSOnet). The proposed algorithm takes parametric input such as node coverage, number of users, location of node and user, operating frequency, etc., and delivers a binary decision for each base station in the network. This determines its state (ON or SLEEP). A dynamic allocation allows users to achieve maximum network lifetime with minimum energy consumption. The proposed optimization algorithm is depicted in the concept diagram in Fig. 1. The proposed BSOnet is given the original network parameters, and the model then outputs which base station may be shut off to save power. Initially, 5 devices close to Base Station 1 are connected to it. Then, 1 device which is close to Base Station 2 is connected to the second base station. The network parameters for this network connection are given to the BSOnet and its output tells us that as the device which is closer to Base Station 2 is also in the range of Base Station 1, Base Station 2 can be shut off and the device can connect to Base Station 1.

II. LITERATURE REVIEW

Lin *et al.* [5] have proposed an Internet of Things (IoT) architecture for allocating resources in a 6G network. They have used a frequency parameter having a value of 100 Gbps. They have also used a nested neural network for the dynamic allocation of resources in the network. In their work, they used a 6G network scenario with resources such as vehicles,

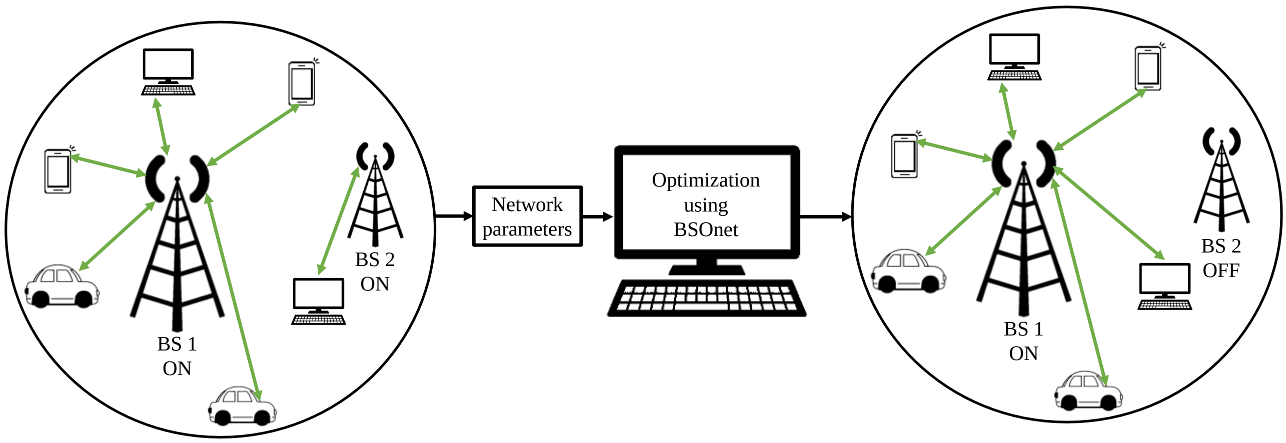

Fig 1: Concept diagram of the proposed optimization algorithm. The initial network parameters are given to the proposed BSOnet and the model then gives an output of which base station may be turned OFF to conserve power consumption.

mobile phones, personal computers, and base stations. They have used an algorithm that combined a nested neural network with a Markov decision-making process. Their algorithm was able to sense the state of the end devices in real-time and different devices were given different priorities for resource allocations. The allocation of resources was increased by about 8 % and the waiting time for the devices was reduced by 7 %. Jain et al. [6] have used the blockchain approach for resource allocation for a 6G network designed using Cybertwin. They have stated that blockchain makes a lot of good contributions to the 6G networks such as keeping a complete track of the resources in the network. It monitors, manages, and allocates resources. They have developed a new optimization algorithm named Quasi Oppositional Search and Rescue Optimization (QO-SRO) which allocates the resources and also has a better convergence rate. Their algorithm obtained a system cost of 4.906 for a file of size 1000 kb in 5 iterations. For around 100 nodes their network obtained a power consumption of 0.878 mW. Their optimization algorithm achieved a system cost of 2.63 and the power consumption was 0.012 mW which was much lower when compared to other methods. Guan et al. [7] have used Deep Reinforcement Learning (DRL) to develop a resource management algorithm. Different resources in the network have been given different slices of the network and the DRL is used to check the requests from the devices and allocate the resources based on the slices. They have divided the problem of resource allocation into two parts, one based on the multi-dimension allocation of resources and the second on the real-time adoption of slices. The satisfaction of the network was increased by up to 20 % using their algorithm. Liu et al. [8] have used the reinforcement learning algorithm and applied the constrained Markov decision-making process for the resource allocation in the network. They have done slicing of the network to reduce the cost. The end-users in the network adapt dynamically to the changes in the network and can also customize the slicing. To adjust to the dynamically changing behaviour of the users the scale and rate of flow network need to adapt continuously. Their model learns from the feedback that they get from the network state to make the most optimal decision. Xu *et al.* [9] employed fog computing system for load balancing and different types of computing nodes are shown and accordingly resource allocation method is designed to satisfy the load balance. Mukherjee *et al.* [10] Energy consumption issue for massive IoT system is addressed. To find the node and its location, it uses distributed artificial intelligence DAI and for optimization it uses convolutional neural networks (CNN) and backpropagation neural network (BPNN) is used. Efficiency in resource allocation for IoT system is calculated in terms of decreased energy consumption. Kibria *et al.* [11] optimization schemes for the network are designed using some data analytics so designing of efficient and dynamic algorithms using machine learning (ML) and Artificial Intelligence (AI). Liu *et al.* [12] proposed new Actor critic to optimize jointly the real time activities of computational resource allocation and radio resource allocation. Simulation mentions this system is better than deep queue network (DQN). Sami *et al.* [13] proposed novel algorithm names IScaler, it is intelligent and upbeat for IoE environment. It provides scaling of resource and placement of service solution. IScaler is custom made for MEC, advancements introduced are deep reinforcement learning (DRL). It provides the self-governing resources for multiapplication scenario. Yang *et al.* [14] mentioned resource management, intelligent service provision and automatic adjustment of network.AI empowered techniques to excellently and efficiently optimize the network. Performance of the system provided in terms of greater training accuracy, reduced computational complexity and enhanced speed.

III. METHODOLOGY

To develop our BSOnet model we have used MATLAB programming software and the network designer was used to design our Neural Network. The design of our proposed model is as shown in Fig. 2. The values of the parameters taken to build our CNN were as follows:

- The number of features were 14. The different features of the network given as input to the model were channel frequency, number of users, transmitter power, receiver power, receiver location, transmitter location, channel noise, packet length, number of packets, load on devices, number of neighbouring base stations, distance from neighbouring base stations, the bandwidth of the network and delay in the network.
- The second layer was a fully connected layer with 12 nodes.
- The third layer was a fully connected layer with 8 nodes.

- The fourth layer was a fully connected layer with 2 nodes.
- The fifth layer was a Softmax activation function. If the output of this layer was greater than 0.5 then the base station was ON else it was OFF.

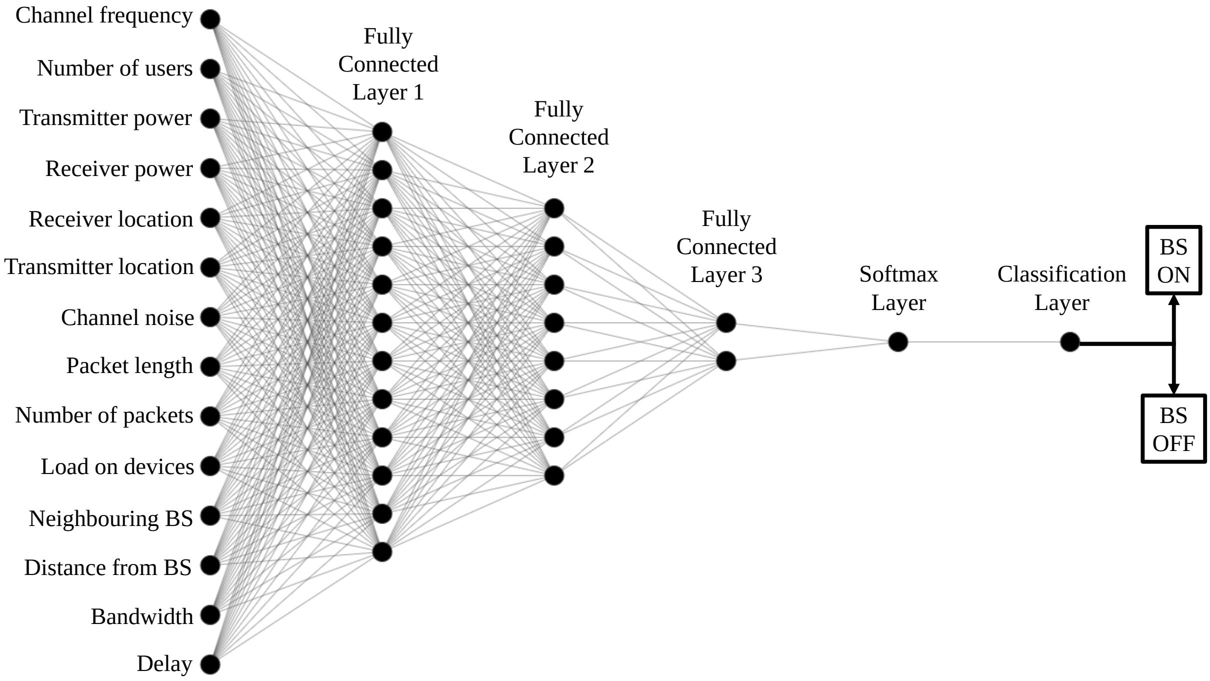

Fig 2: The network architecture of the proposed BSOnet neural network. The input layer consists of 14 nodes each taking in different parameters. The second, third, and fourth layers are fully connected layers with 12, 8, and 2 nodes respectively. This is followed by a Softmax function and finally the classification layer.

- The final layer was the classification layer that gave the final output based on the value of the Softmax function.

$N_{out} = [\ (N_{in} + (2 * padding) – kernels) / stride] + 1$ (1)

Equation 1 shows the standard equation of the convolutional network.

To train our model we first created a dataset where the values of the number of users and base stations and their locations along with the number and distance from neighbouring base stations were varied. The dimensions of the simulated area of the network were 1000 X 1000. Further, the load on devices, power of the transmitter, power of the transmitter, channel noise, and the number of packets were also varied. This was done by running a code for parameter generation multiple times on MATLAB. Based on the generated parameters, they were divided into two classes namely base station ON and base station OFF. The network as mentioned above was then trained on this dataset. The dataset was loaded into the appropriate location in the deep network designer available on MATLAB and the model was trained.

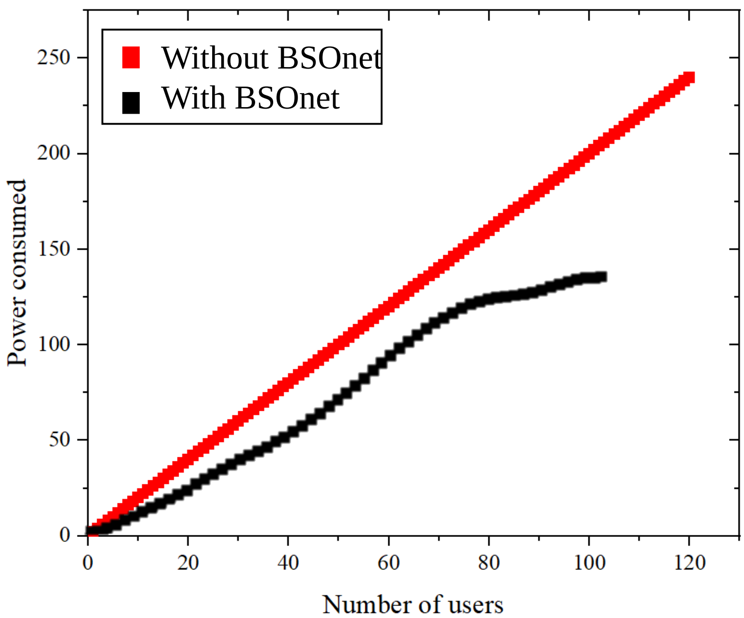

Fig 3: Comparison of power consumption in a network with and without our proposed Nonet. In the network with BSOnet the power consumption, despite the increase in number of users remains lower than a network without BSOnet

The values for the 6G parameters were set as follows:

- Channel frequency = 100 THz
- Network bandwidth = 100 GHz
- Delay in the network = 5 X 10^{-5} Sec

IV. Results and Discussions

We tested our network with the parameters having the following values. The power of the transmitter was 30 dB, and the power of the receiver was 2 dB. The location of the transmitter and receiver was generated using the random function in MATLAB in an area of 1000 X 1000 dimensions. The channel noise was -0.5 dB. The number of packets was 100 and the load on each device was 20 dB. Each base station was allowed to have 40 partner nodes.

We obtained the graph of the power consumed in the network with and without BSOnet. It can be seen from Fig. 3 that the power consumed by the devices without BSOnet increased linearly with the increase in the devices. Each device consumed 2 dB of power resulting in an increase in the power consumed. Whereas when our BSOnet was used, the graph of the power consumed increased non-linearly. Initially, for the first few users, the power increased gradually but it can be seen that around 90 to 100 users the power consumption becomes saturated. It is estimated that at a certain point the consumption may become completely stable around a fixed power. The power consumed in the network with BSOnet was also lower than that of when there was no BSOnet.

As the scope for further work, the network can be designed to optimize different parameters for 6G networks. Also, as data transmission is faster than audio transmission, this paper focused on the communication of data. But in the future audio transmission can also be used to test the proposed algorithm.

V. Conclusion

Thus in this manuscript, we have proposed a deep learning network to optimize the allocation of resources to base stations for a 6G communications network. The 6G network was simulated using the standard values for the 6G parameters. A neural network named Node Optimization Network (BSOnet) was designed on the MATLAB software and a dataset with varying values of parameters was fed to it for training. This network when deployed in the simulated 6G network showed a decrease in power consumption. This network is a step in the direction of optimization of the developing 6G networks and with this study, we hope to provide the scientific community with a pathway to do further research in this area.

Declarations

Funding information
No funding was involved in the present work.

Conflicts of interest
Authors P. Kamble and A. N. Shaikh declare that there has been no conflict of interest.

Code availability
Code will be made available upon reasonable request to the authors.

Authors' contributions
Conceptualization was done by P. Kamble (PK) and A. Shaikh (AS) . All the simulations were performed by PK. Manuscript writing - original draft preparation PK. Review and editing was AS. Visualization work carried out by PK.

Ethics approval
All authors consciously assure that the manuscript fulfills the following statements: 1) This material is the authors' own original work, which has not been previously published elsewhere. 2) The paper is not currently being considered for publication elsewhere. 3) The paper reflects the authors'own research and analysis in a truthful and complete manner. 4) The paper properly credits the meaningful contributions of co-authors and co-researchers. 5) The results are appropriately placed in the context of prior and existing research.

Consent to participate
This article does not contain any studies with animals or humans performed by any of the authors. Informed consent was not required as there were no human participants. All the necessary permissions were obtained from Institute Ethical committee and concerned authorities.

Consent for publication
Authors have taken all the necessary consents for publication from participants wherever required.

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