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Modified-LSTM and feed forward neural network enabled resource allocation for 6G wireless networks

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ABSTRACT

The 6G wireless networks utilize terahertz (THz) frequency and intended to tremendously dynamic and diverse applications with deep learning enabled network, harvested significant attention and able to solve complex problems. Efficient resource allocation is a key requirement of next generation wireless networks. This research focuses on the resource allocation optimization challenge which includes storage, computing power, bandwidth and memory in the milieu of 6G wireless networks with device-to-device (D2D) communication enabled. The proposed model uses modified long short-term memory (mLSTM) and feed forward neural network to allocate resources to various tasks as per requirement such as information access, audio/video streaming, information access and productivity activity applications. The proposed work focuses on network parameters like channel noise, signal to noise ratio (SNR), distance from base station and includes D2D communication decisions to improve network performance. This research gives a novelty learning based solution for resource allocation for 6G wireless networks which contributes to the enhancement of next generation wireless communication networks. The lowest computing power utilized is 1%, Bandwidth utilized is 3% of total bandwidth and 2% storage.

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1. INTRODUCTION

In the 5G era and beyond networks there is a great demand of high-speed data transfer, efficient resource utilization and seamless connectivity. 6G wireless network promise revolutionize wireless communication, unparalleled data rates massive device connectivity ultra-low latency however its ambitious goals pivot the development of innovative resource allocation strategies which can effectively manage the delimited resources available in the wireless networks. 6G wireless network will have new avenues. 6G wireless network is intended to provide global coverage, which will cover sea, ground and air. It will provide full spectrum which includes THz, mmWave and sub 6 GHz. Artificial intelligence, machine learning and deep learning technologies will be combined to 6G wireless networks for automation and network management. The evolution towards 6G networks presents unique challenges that demands a more intelligent and comprehensive approach to resource allocation [1]. One of the key challenges is the efficient management of various resources including storage, computing power, bandwidth and memory considering the heterogeneous nature of devices and applications. Inclusion of device-to-device (D2D) Communication gives a new dimension to resource allocation. D2D communication stands for device-to-device communication, which allows devices directly to communicate with each other bypassing the need for central base station. Novel techniques such as deep learning can influence this technology [2]. Figure 1 shows the proposed resource allocation for the 6G network.

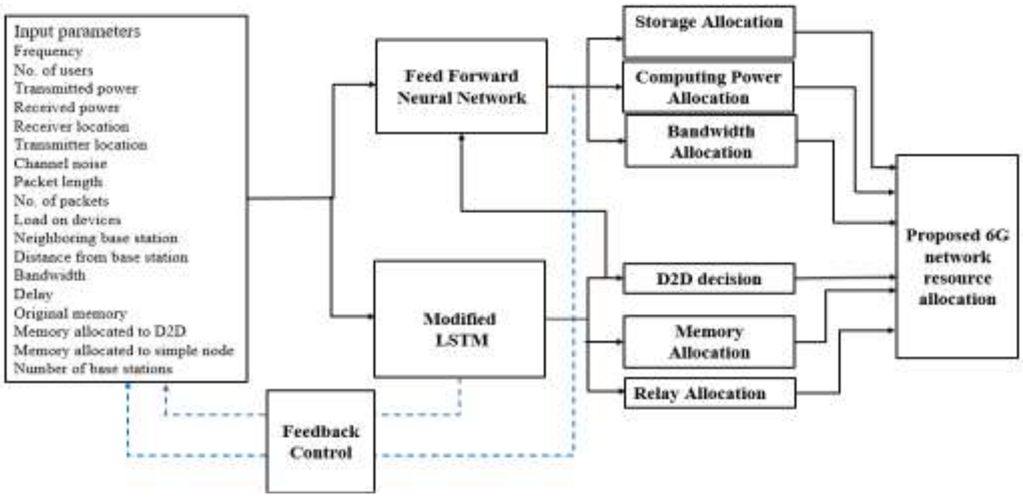

Figure 1. Resource allocation for 6G wireless networks

In this research the author proposes a deep learning enabled framework for resource allocation for 6G wireless network with D2D communication capabilities. Authors contributions are threefold: (1) Integration of a novel neural network architecture with various network parameters such as channel noise, distance from base station and signal to noise ratio to optimize resource allocation. (2) An intelligent decision making process for D2D communication based on device proximity and network conditions. It uses modified long short-term memory (mLSTM) architecture, which use tanh as state activation function and hard sigmoid as gate activation function for accurate D2D decision. Relay decisions were taken based on signal to noise ratio (SNR) values between the nodes. (3) Further input parameters and D2D decision is used in the task aware resource allocation strategy which considers the various requirements of different applications including audio video/streaming, communication, information access and productivity applications. Feed forward network is a type of artificial neural network which has input layer as various tasks, two hidden layers each consisting of ten neurons and output layer is of three neurons which gives the predictive probabilities for storage computing power and bandwidth.

Many researchers have contributed to the field of resource allocation in wireless networks. Toka *et al.* [3] proposed optimization of power allocation in cognitive radio networks using game theoretical approach. Ye *et al.* [4] proposed Reinforcement learning based framework for dynamic resource allocation and spectrum access for 5G networks. Li *et al.* [5] demonstrated Heuristics algorithm for joint optimization of radio and computational resources in multi access age computing systems. These initially focus on specific aspects of resource allocation to serve the requirements of existing wireless technologies; these contributions have significantly advanced the field.

Stan *et al.* [6] compared to standard systems; the paper gives a weighted proportionally fair solution for radio resource allocation in 5G offloading scenarios that equilibriums performance fairness. Dai *et al.* [7] has proposed deep learning using optimal computation offloading and resource allocation for 5G networks. It also significantly reduces energy consumption. Alnakhli *et al.* [8] have proposed optimization of bandwidth allocation and power control in 6G multi-unmanned ariel vehicle networks using two step algorithms which improve data rate and energy efficiency. Tzanakaki *et al.* [9] have presented AI enabled dynamic resource allocation using neural networks and management and orchestration optimize resource allocation and improve system performance. Li *et al.* [10] have demonstrated the federated learning platform for 6G using block chain technology to enhance dynamic spectrum management with high detection accuracy and reward distribution across 30 secondary users. Hu *et al.* [11] have proposed a novel framework for resource allocation in unmanned ariel vehicle-6G networks, achieves high slice acceptance rates compared to existing methods. Kim [12] have discussed resource allocation using deep reinforcement learning, achieves 78.90% data volume and latency compared to static allocation.

The following sections of this manuscript will provide a detailed description of proposed structure of papers which includes the system model neural network architecture and resource allocation algorithms. This paper provides comprehensive evolutions and comparisons with existing techniques, presenting the effectiveness of the given approach in terms of minimizing noise maximizing SNR and improving overall networks performance. Finally, authors discuss the potential impact and societal benefits of their work, paving the way for more efficient and intelligent resource management for future 6G networks.

2. METHOD

The proposed methodology involves the following key steps: The first step involves simulation of various 6G network parameters, Number of users per base station, frequency, transmit power, receive power, channel noise, coverage area, packet length, number of packets, partner nodes, distance from base station, bandwidth [13]. These parameters are generated randomly within realistic ranges to mimic real world network scenarios the simulation is performed for multiple iterations to cover diverse scenarios.

The framework includes a decision-making process for enabling device to device D2D communication based on distance from the base station and the number of partner nodes [14]. If the distance is less than a predefined value (e. g. 20 meters) and the number of partner nodes are below a specified limit (e.g. 10 m), D2D communication is enabled. This approach makes use of the potential benefits of D2D communication, such as improved resource utilization and reduced latency while considering the network conditions and device proximity [15]. Whether a node can function as a D2D communication is decided using a deep learning algorithm (mLSTM).

The mLSTM is a Neural Network category, which is widely used for sequential modeling tasks. mLSTM is used for efficient D2D decision making. mLSTM architecture involves several gate mechanisms, which are given by following equations [16]–[18].

$$f_t = \mathrm{h\_}\sigma(W_f X_t + U_f h_{t-1} + b_f) \tag{1}$$

$$i_t = h\_\sigma(W_i X_t + U_i h_{t-1} + b_i) \tag{2}$$

$$O_t = h\_\sigma(W_o X_t + U_o h_{t-1} + b_o) \tag{3}$$

$$C_t' = \tanh(W_c X_t + U_c h_{t-1} + b_c) \tag{4}$$

$$C_t = f_t \odot \mathrm{C}_{t-1} + \mathrm{i}_t \odot \mathrm{C}_t' \tag{5}$$

$$h_t + O_t \odot \tanh(C_t) \tag{6}$$

where:
f_tf, i_t, O_t, C_t', are the forget, input, output gates and candidate cell states respectively
C_t is the cell state
h_t is the hidden state
W and b are the weight matrices and bias vectors for the respective gates
h_σ is the hard sigmoid activation function
tanh is the hyperbolic tangent activation function

The framework generates random signal to noise ratio SNR values for different parts between nodes in the network [19]. Maximum SNR for each node is calculated and a source destination matrix is created, containing the corresponding SNR values. However, only the SNR values above the average are considered, as these represent the more favorable communication links [20].

Signal strength with respect to background noise level is measured as SNR. It is expressed in decibels (dB). It is calculated using (7) [21].

$$SNR = 10\log_{10}(\frac{P_{signal}}{P_{noise}}) \tag{7}$$

where:
P_{signal} is the power of the signal
P_{noise} is the power of the noisy

The core of the resource allocation framework is a feed forward neural network with two hidden layers each containing 10 neurons [22]. The input to the neural network is one hot encoded representation of different tasks, such as communication, audio streaming, video streaming, information access, banking and finance navigation and productivity content generation. The neural network output is represented in the form of predicted probabilities for computing, storage and bandwidth allocation [23]. The neural network is trained using a supervised learning approach, where the desired output probabilities for each task are provided as training data. The training process includes minimization of error between predicted probabilities and the desired probabilities using a correct optimization algorithm, such as back propagation [24]. The framework calculates the memory, storage, computing and bandwidth allocated for the given task based on predicted probabilities which are obtained from the neural network. These resource allocations are tailored to the specific requirements of each task, ensuring efficient utilization of available resources.

The framework uses bandwidth and channel noise to calculate the bandwidth and noise distribution accordingly. Ensure reliable data transmission, mitigating the impact of noise on network performance is an aim of this step [25]. The proposed methodology includes theoretical justification and empirical evaluations to validate the deep learning-based resource allocation approach effectiveness. The algorithm implementations, network simulation parameters and neural network architectures are thoroughly documented, enabling researchers to duplicate and build upon the presented work.

Predicted probability from the neural network and the total available bandwidth is used to calculate allocated bandwidth to a particular task or application [26].

$$Bandwidth_{alloted} = P_{bandwidth} * Total_{bandwidth}$$

where:

$P_{bandwidth}$ is the predicted probability for bandwidth allocation from the neural network. $Total_{bandwidth}$ is the total available bandwidth in the network

The resource allocation problem can be called a problem of optimization. The objective is to maximize the overall network performance or utility while fulfilling various constraints. that is fine various constraints. The optimization problem can be represented as:

$$\text{Maximize:} U(R_1, R_2, \ldots., R_N) \tag{8}$$

subject to:

$$\sum_1^N R_i \leq R_{total} \tag{9}$$

$$R_i \geq 0 \quad \forall_i \in \{1,2, \ldots. N\} \tag{10}$$

where:
U is the utility function representing network performance
R_i is the resource allocation for the i-th task or application
R_{total} are the total available resources
N is the number of tasks or applications.

The sensation results show the proposed deep learning enabled resource allocation framework for 6G networks with D2D Communication capabilities. A sample network scenario with 10 nodes, a base station and simple node performing various tasks such as banking communication navigation audio streaming information access video streaming and productivity is shown in Figure 2.

3. RESULTS AND DISCUSSION

Proposed deep learning-enabled resource allocation framework for 6G networks with D2D communication capabilities was rigorously evaluated through extensive simulations involving a sample network scenario with 10 nodes. By incorporating various network parameters such as channel noise, distance from the base station, and SNR into the mLSTM based decision-making process, more intelligent and efficient resource management is achieved by this framework. This approach not only outperforms conventional methods which often rely on a limited set of parameters but also determines the significant benefits of using D2D communication, which is deep learning enabled based on device proximity and network conditions. This is particularly advantageous in the milieu of 6G networks capability, where the seamless integration of a diverse range of devices and applications is a critical requirement.

The framework also ensures reliable data transmission and minimizes noise effects by optimizing relay paths between nodes considering the respective SNR values of each link. The values of SNR for the relay links ranges from 34 dB to 40 dB in the calculated results. Figure 3 represents the 6G wireless network scenario indicating a spatial distribution of various network elements in a two-dimensional coordinate system where the X-axis shows the horizontal location in meters and the Y-axis shows the vertical location in meters. Base station, simple nodes and D2D nodes are shown by red cross, green stars and green stars with circles respectively. The positioning of these elements is crucial for planning and optimizing network coverage, connectivity, and performance. These nodes, including a base station and others performing tasks such as banking, communication, navigation, audio streaming, information access, video streaming, and productivity applications, were subjected to a thorough analysis. Figure 2 represents the allocation for storage, computing power and bandwidth allocation for various tasks.

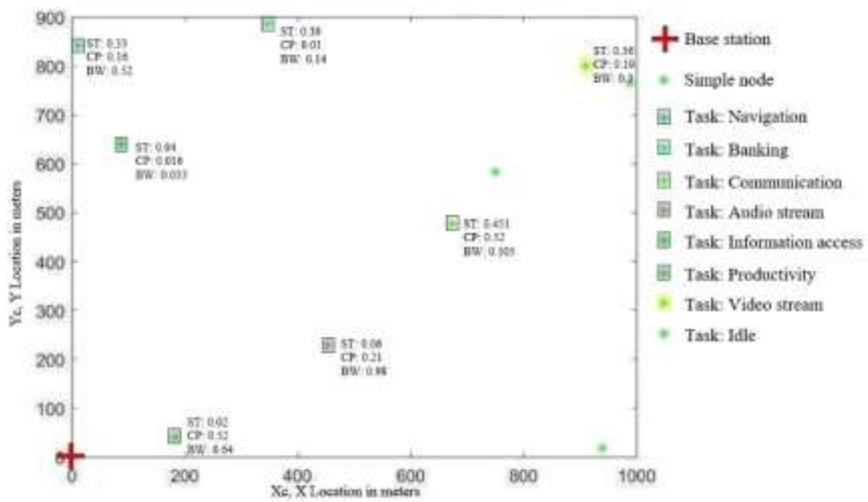

Figure 2. Storage, computing, and bandwidth allocation for various tasks

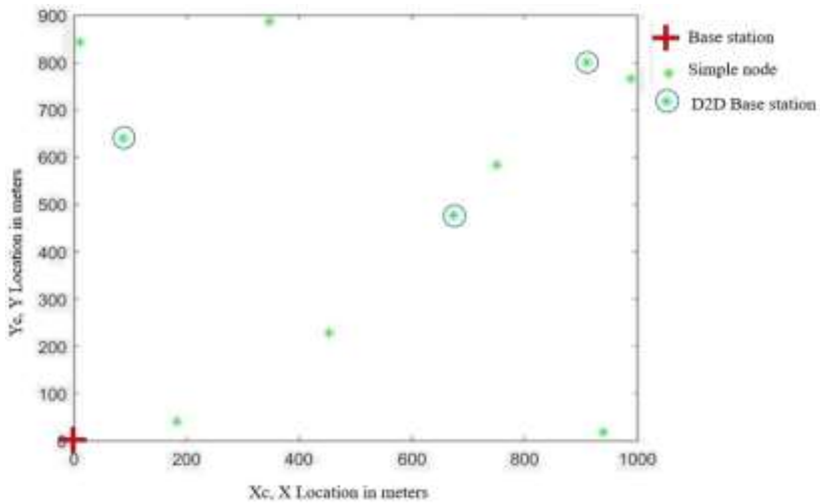

Figure 3. 6G wireless network scenario

The results revealed that the framework could efficiently allocate resources storage, computing power, and bandwidth based on the specific demands of each task. For instance, the node dedicated to banking tasks was assigned higher resources for storage (0.451), computing power (0.52), and bandwidth (0.505) compared to the node engaged in navigation tasks, which received significantly lower allocations (storage: 0.04, computing power: 0.016, bandwidth: 0.033). Figure 4 depicts the relay links between nodes, with the SNR values indicated for each link.

Additionally, the framework's intelligent decision-making process, which enabled D2D communication based on device proximity and network conditions, was found to significantly enhance resource utilization and reduce latency. Furthermore, the optimization of relay paths using SNR values contributed to efficient resource allocation and ensured reliable data transmission, with SNR values for the relay links ranging from 30 dB to 40 dB, effectively mitigating the impact of noise on performance of network. The findings of this research underline the effectiveness of the proposed mLSTM enabled resource allocation framework which addresses the unique challenges posed by 6G networks, especially those incorporating D2D communication capabilities. These frameworks key advantage is its ability to adapt to diverse network conditions, device characteristics, and application requirements, which sets it different from traditional static resource allocation methods.

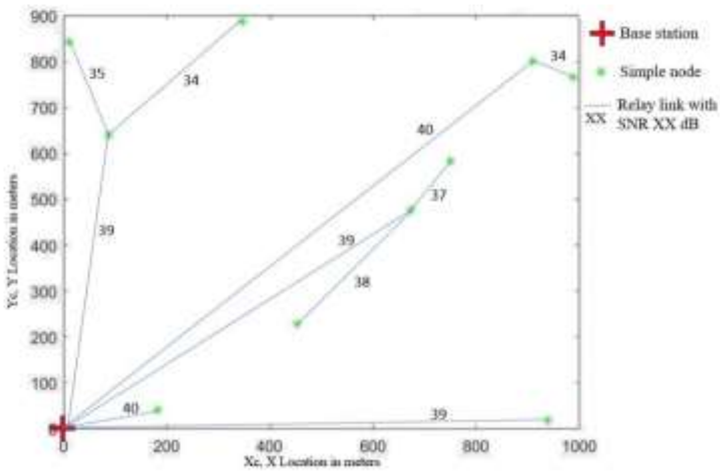

Figure 4. SNR based relay allocation for 6G wireless networks

Despite the promising results established by the proposed framework, there are some limitations that need further exploration. Notably, factors such as mobility, scalability, and energy efficiency were not the primary focus of this study, though they are essential for enhancing the framework's applicability in real-world scenarios. Future research could explore these aspects in greater depth to improve the overall robustness of the framework. Additionally, integrating more advanced deep learning techniques such as federated learning or multi-agent reinforcement learning could further improve the framework's decision-making capabilities and adaptability to dynamic network conditions. Furthermore, blockchain technology or other distributed ledger solutions could strengthen the decentralized management of resources and security in 6G networks.

This research introduces a novel mLSTM based framework for resource allocation in 6G wireless networks, particularly those with D2D communication capabilities. By leveraging deep learning and integrating key network parameters such as device proximity, channel noise, SNR and the framework effectively allocates essential resources, including, computing power, storage, bandwidth, and memory tailored to the diverse tasks and network conditions encountered in 6G networks. The framework's intelligent decision-making process for enabling D2D communication, coupled with the optimization of relay paths based on SNR, significantly enhances network performance and resource utilization. The potential impact of this work is substantial, as it could lead to significant improvements in user experiences, enable new applications, and drive the advancement of next-generation wireless communication systems, ultimately contributing to the realization of a more connected and efficient future.

4. CONCLUSION

This research examines a critical challenge in the evolution towards 6G wireless networks - the efficient allocation of resources, including computing power, storage, bandwidth, and memory. The proposed mLSTM learning-based framework addresses this challenge which effectively distributes the limited resources to varied tasks and applications, considering the unique requirements and network conditions of 6G systems. The core of the framework is a deep learning-enabled decision-making process that leverages various network parameters, such as channel noise, SNR and device proximity, to optimize resource allocation. The intelligent integration of D2D communication further enhances resource utilization and reduces latency of 6G networks.

Novel deep learning based solution is provided to the ambitious goals and unique challenges of 6G networks whereas previous research has explored resource allocation with respect to existing wireless technologies. The framework can adapt to diverse scenarios and prioritize critical applications showcases its potential to significantly improve user experiences and enable new use cases that were not feasible with earlier generation networks. The findings of this study serve as a strong foundation for future research in the domain of resource management for 6G and beyond. Researchers are encouraged to build upon this work by exploring advanced deep learning techniques, incorporating mobility and scalability factors, and investigating the integration of emerging technologies like blockchain to further enhance the security and decentralized management of resources in the 6G ecosystem.

This research addresses the challenge of efficient resource allocation. A more connected, adaptive and intelligent future wireless communication landscape can be realized by this research. Readers are recommended to endorse and actively participate to promote the advancement of solutions, which will influence the next generation wireless networks.

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