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Intelligent traffic load optimization and channel allocation in next-generation wireless networks using neural networks

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Abstract: We explore neural network-based optimization techniques for resource allocation and management in dense wireless networks in the research. The growing demand for efficient communication in contemporary wireless systems makes the isolation of traffic load and channel distribution essential for guaranteeing the best possible development of the network. The new approach is based on artificial neural networks and proactively assigns the available frequency-related channels to users according to their traffic load. The neural network is trained on the data to predict the optimal channel allocation strategy based on a dataset representing users' traffic regarded as demand. Performances are measured in terms of network efficiency, channel utilization, percentage of collisions, and energy consumption. The findings reveal a marked enhancement in the network's performance parameters, including optimization of bandwidth usage, minimization of collision occurrences, and an overall increase in energy efficiency. This work demonstrates neural networks' capabilities to tackle next-generation wireless network challenges, pointing to a direction of smarter, more effective, and efficient communication systems.

Keywords: *Channel allocation, Collision reduction, Dense wireless networks, Energy consumption, Frequency channel management.Intelligent communication systems, Machine learning, Network efficiency, Neural networks, Next-generation wireless systems, Resource allocation, Traffic load optimization.*

1. Introduction

The world of wireless communication networks, lately, has been changing rapidly because of the growing need for connectivity. The explosion of IoT devices, smart applications and mobile users has given rise to increasing signs of network congestion and resource mismanagement. The conventional resource allocation schemes within wireless networks (FDMA, TDMA, and CDMA) can work well in simple conditions, but as we move into a world of high density and diverse traffic, more dynamic and flexible approaches that can adapt are needed. The next-generation of wireless technology — 5G and beyond — is expected to solve many of these problems. However, such systems call for more advanced strategies of dynamic spectrum management, optimal channel allocation, and interference reduction. However, recent developments in machine learning (ML) and artificial intelligence (AI) methods, especially neural networks, are promising approaches that offer the potential of real-time decision making driven by historical and real-time data. Stable resource allocation in dense wireless networks A neural network-based approach Our main focus is on traffic load management, user efficiency and energy saving in the HDNs, where users have time-varying traffic load and different QoS requirements. The proposed method facilitates dynamic allocation of the network resources according to the user traffic load while minimizing the energy per user consumption. The findings suggest that neural networks provide a more advanced approach to resource allocation strategies when compared to

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classical approaches, resulting in improved network efficiency and energy savings. In this paper, we present a deep neural network approach that leverages variable traffic workloads to best assign users while avoiding interference in the network. We assess the model performance through extensive simulations and show that it outperforms existing solutions in terms of throughput, energy efficiency, and overall system performance.

2. Lecture Review and Related Work

The problem of resource allocation in wireless communication networks is a classic topic that has been widely considered as it is crucial to guarantee that finite resources including bandwidth and power are utilized efficiently. As networks are being transformed to accommodate millions of devices and diverse types of traffic, 5G and IoT not only Open issues in scheduling but also the evolution of heterogeneous networks has made the challenge of effective resource management more acute. In earlier days, resource allocation methods used deterministic schemes to assign channels (or time slots) to users. These approaches were efficient only in static low-density formation, however, they performed poorly in the dynamic high-density networks. With the arrival of heterogeneous networks (HetNets) and ultra-dense networks (UDNs), also came the challenges surrounding interference management, mobility and heterogeneous and variable traffic patterns -- thus, the need for adaptive, intelligent solutions. In recent years, machine learning methods, in particular supervised learning algorithms, have found their way into wireless communication systems for use in resource allocation. Among such techniques, neural networks are widely recognized for their capability to generate multi-faceted relationships between the data features, their potential to learn from historical data in complex linear rather than stated relationships. Neural networks have been extensively used for optimization problems with wireless networks, which could be channel allocation, interference management, and traffic prediction, etc. The work of Zhao, et al. [1] brought a considerable advancement in this direction as they employed deep reinforcement learning to dynamic spectrum management in cognitive radio networks. The model therefore had the ability to respectively learn and adapt to the ever changing environmental condition which was resulting in a better utilization and lesser interference among the overall spectrum. Kaur, et al. [2] for instance, approached this problem using recurrent neural networks (RNNs) for dynamic channel allocation, showcasing the ability of such models to respond to traffic fluctuations as occur in real time. Moreover, Ghosh [3] proposed a hybrid model using convolutional neural network (CNN) and optimization techniques such as genetic algorithms. Their model achieved higher spectral efficiency and throughput than conventional methods. Ashwin, et al. [4] showing the usefulness of reinforcement learning in resource allocation at WSNs level by improving the energy efficiency and reducing latency. While there is an increasing number of papers describing experiences in various setups, the optimization of performance in dense networks who experience heterogeneous traffic and environmental aspects remains elusive. To tackle these issues, this paper introduces an advanced neural network framework that incorporates traffic load management and energy efficiency into the resource allocation process. The application of machine learning to resource allocation in wireless networks is not a new one. However, the complexity of modern networks that are growing rapidly at an accelerating rate is giving rise to burgeoning areas of inquiry in this regard. AI and ML techniques such as neural network have brought a new trend of dynamic management of network resources. In Ahmed, et al. [5] authors optimized spectrum sharing in cognitive radio networks via deep neural networks. To optimize the system performance for enhanced throughput and throughput interference management, they used DNNs to predict available channels given user demand and environment state [6]. A deep reinforcement learning (DRL) approach to dynamic resource allocation in 5G networks towards energy consumption and throughput maximization. Energy consumption optimization is the one of the biggest challenges in ultra dense wireless networks [7]. Used DL models to forecast energy usage trends along with the energy-preserving scheduling protocols of 5G mobile networks. Because their model focuses on the balance of throughput and energy efficiency to provide optimal energy usage while fulfilling performance requirements. Recent works also study the use of multi-agent reinforcement learning (MARL) for distributed resource allocation in networks [8]. Introduced a MARL approach for load balancing in ultra dense networks in which multiple agents interacted with the network for resource allocation. Compared to the standard algorithms, their model exhibited much better fairness with respect to load distribution. They complemented deep Q-networks (DQNs) with traditional optimization algorithms to enhance user scheduling and channel allocation in heterogeneous networks in Yu, et al. [9]. This hybrid approach could adapt (to the dilution) to the different network conditions and provide higher efficiency in that measure by reaching higher throughput but also consuming less energy, compared to traditional algorithms [10]. -Based on neural network resource allocation in IoT networks. It's supervised learning and unsupervised learning model concept was used to combine their efforts to optimize bandwidth allocation while minimizing interference. Despite similar tendency on reference [11] that using support vector machines (SVMs) to optimize interference management in 5G networks. This growing body of work showcases the canny use of machine learning, and neural networks in particular, to effectively reallocate resources in contemporary wireless communication networks. While research focusing on spectrum allocation, throughput optimization, or energy efficiency is common, a comprehensive solution considering the balance between traffic handling and the optimization of user and energy efficiency is rarely available [12-14]. This contribution generalizes the previous work by developing a common framework encapsulating all these aspects, providing a cohesive solution to collision-free, dense, next-generation wireless networks.

3. Proposed System Model

This resource allocation problem is addressed by the proposed system model below, which is based on a neural network framework for dense wireless networks. The elements described in this section are responsible for traffic load generation, resource allocation (a neural network), collision detection and energy consumption optimization to increase network performance. The real-time nature of the model makes it capable of adapting quickly to changing network conditions, thus ultimately leading to a better experience for the user and more efficient utilization of network resources. The system model consists of the following critical components, which in turn ensure that users are appropriately allocated resources, collision is minimized, and energy consumption is optimized. Traffic Load Generation, Resource Allocation Using Neural Network, Channel Allocation Process, Collision Detection, Energy Consumption Calculation, Efficiency Metrics. Table 1 Parameters Values. The following is the block diagram of the system model proposed:

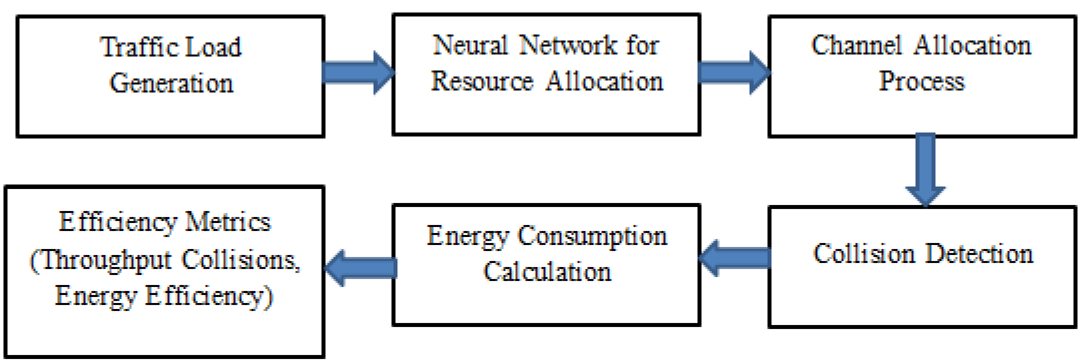

Figure 1.
Below is the block diagram for the proposed system model.

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Table 1.
Parameters Values.

Parameters	Values
Number of Users	100
Number of Channels	20
Maximum Bandwidth per Channel	10 Mbps
Energy Consumption Factor	0.5 Joules per Mbps
Number of Hidden Layers	1
Neurons per Hidden Layer	10
Activation Function	Sigmoid

3.1. Explanation of Each Block

- Traffic Load Generation: It randomly allocates traffic loads (demand) of users within ranges to simulate user traffic. Because the traffic is random, the system can handle a variety of real-world usage rates, and the neural network can train on different loads. This block here replicates the network user traffic load. Each user has a traffic load randomly chosen from values in the range of 1 to 20 Mbps. This load translates to the data that a user wants to send at a time slot. This synthetic traffic load models realistic user behavior and provides input for resource allocation.

$$T_i = rand\ (1,20\ )\ \forall\ \mathrm{i} \in \{1,2,\dots,N_{\text{users}}\} \qquad (1)$$

Where:
T_i is the traffic load for user i in Mbps.
$N_{\text{users}}$is the total number of users in the network (e.g., 100 users).

- Neural Network for Resource Allocation: We use a neural network to predict the best distribution of resources. It takes the traffic load as input and outputs the channel allocation. Based on the traffic load, optimal channel allocation can be determined, and a neural network is trained with real or simulated historical data using this information. The neural network is what predicts the resource allocation for each user given each user's traffic load. In this approach, we consider the traffic load as input and channel allocation as output, optimizing the assignment according to the load distribution. This makes sure that how many users assign resources (channels), optimally assigned, to minimize congestion and accomplish throughput..

$$\hat{C}_i = f(T_i\ ; W\ ;\ b) \qquad (2)$$

Where:
$\hat{C}_i$ is the predicted channel allocation for user ii.
f(·) is the neural network function (e.g., feed forward neural network).
T_i is the traffic load for user ii.
W and b are the weights and biases of the neural network.

- Channel Allocation Process: Once resource allocation is acquired, users are allocated subsequent channels according to the predictions generated through the neural network. This allocation reduces the likelihood of collision and guarantees that available bandwidth is used efficiently. This block is responsible for assigning channels to users based on the predictions. Channel interference is minimized in this allocation. It distributes the channels in a round-robin manner according to the expected load on each user. This will blister the load and congestion.

$$\mathrm{C_i} = \ mod\ (i, N_{\text{channels}} + 1) \qquad (3)$$

Where:
$\mathrm{C_i}$ is the channel allocated to user ii.
$N_{\text{channels}}$is the total number of channels available.

- Collision Detection:
  Multiple users are assigned to the channel and their traffic load exceeds the maximum bandwidth. The condition causes a collision which leads to network inefficiencies. This block detects collision when more than one user is assigned to the same channel. Whenever there is a collision there is

an overload of bandwidth which can reduce the quality of the network. It makes sure that a user cannot spend more than the maximum amount of bandwidth of a channel, enforcing a collision when it's needed.

$$\text{Collision}_{\text{k}} = \begin{cases} 1, & if \sum_{i=1}^{N_{\text{users}}} 1C_i = k > B_{max} \\ 0, & \text{otherwise} \end{cases} \qquad (4)$$

Where:

$1C_i$ is an indicator function that equals 1 if user ii is assigned to channel k, and 0 otherwise.

B_{max} is the maximum bandwidth per channel (e.g., 10 Mbps)

- Energy Consumption Calculation: According to the traffic load of each user, the system calculates the energy consumed by each user. Then, the total energy consumption is accumulated and used to evaluate the network-level energy utilization performance. This also contributes to the optimization of energy consumption of all users, reducing wastage. This block simulates the energy usage of the network. The traffic load (i.e., the amount of data each user transmits) is proportional to the amount of energy consumed by each user. This is the total energy consumption, which is the sum of energy for all users. With the visit of each node, this step will optimize the total energy consumption in the overall network helping to gather how much energy is consumed by the entire network.

$$\text{E}_i = \alpha \, . \, T_i \qquad (5)$$

Where:

$\text{E}_i$is the energy consumption for user i.

α is a constant representing the energy consumption factor (e.g., 0.5 Joules per Mbps).

$.\, T_i$ is the traffic load for user i.

$$\text{E}_{\text{total}} = \sum_{i=1}^{N_{\text{users}}} \text{E}_i \qquad (6)$$

- Efficiency Metrics: Efficiency Metrics the efficiency metrics we provide help quantify the performance of the network. It measures the number of successful allocations, the collision rate, and the total amount of energy consumed. By comparing the calculated efficiencies before optimization and after optimization, we can assess and evaluate the effectiveness of this outlined approach to system model. This block calculates throughput, collision, and energy efficiency of the network. It also compares performance before and after optimization. It offers information on key performance indicators (KPIs) for evaluating network performance and efficiency.

Before Optimization:

$$\eta_{\text{before}} = \frac{\text{Total Users}}{\text{Available Channels}} \, X\,100 \qquad (7)$$

After Optimization:

$$\eta_{\text{before}} = \frac{\text{Successful Allocations}}{\text{Total Channels}} \, X\,100 \qquad (8)$$

This system model efficiently simulates resource allocation, collision detection, and energy consumption in a wireless network, aiming to enhance overall network performance and advance energy efficiency.

4. Simulation and Results

In a proposed system model, several plots were produced to analyze performance metrics like Traffic Load, User Efficiency, Energy Utilization, and Efficiency Comparison (Before vs. After

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Optimization). This allows for easy comparison between the performance of the network before and after the optimization process. Here are each of the results and its respective plots, explained in thorough-going, sequential detail.

Figure 2. User Traffic Demand (Scatter Plot). Follow the scatter plot of traffic load per user (in Mbps)—showing the dense network. Each point corresponds to a specific user traffic load. The x-axis refers to the user index and the y-axis represents the traffic load in Mbps. For each user the data is randomly generated from 1 to 20 Mbps. This plot illustrates how diverse the traffic demand is among different users. It allows us to visualize how the traffic is distributed before applying any optimization or resource allocation.

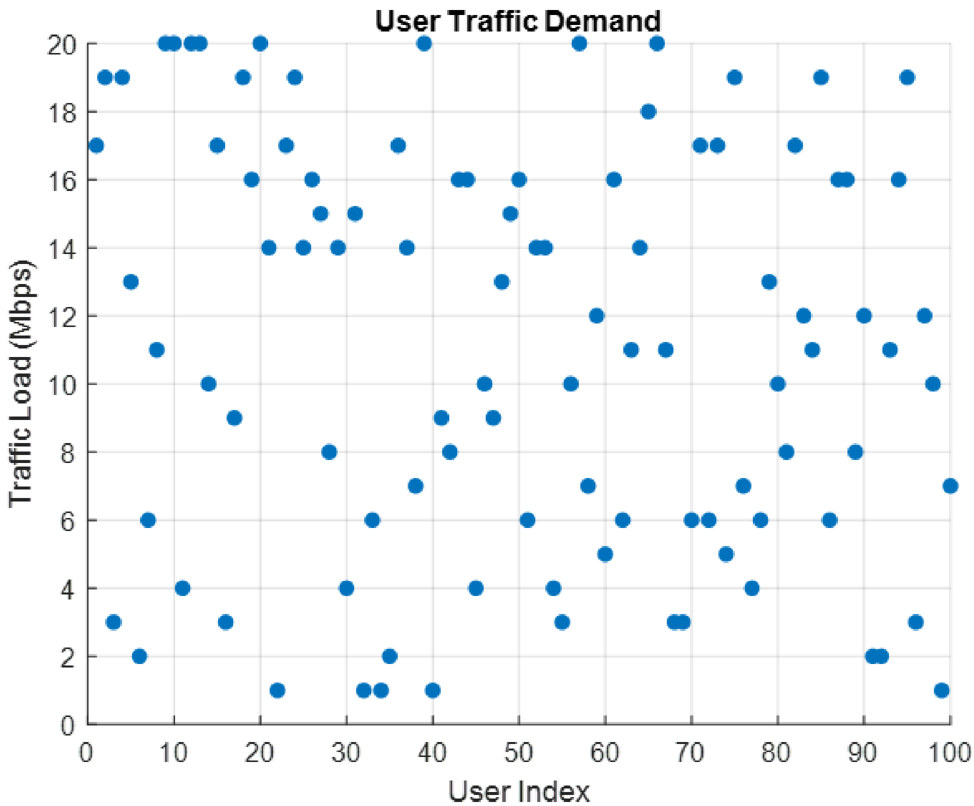

Figure 2.
User Traffic Demand (Scatter Plot).

Figure 3. Channel Utilization After Neural Network Allocation (Bar Chart). This bar chart shows the number of users assigned to each frequency channel after resource allocation by the neural network. The x-axis corresponds to the channel indices, and the y-axis shows the number of users assigned to each channel. The bar height represents how many users are using each channel after the neural network allocation. The bars help visualize the distribution of users across channels. If a channel has too many users (higher bar), it might indicate potential congestion or overuse.

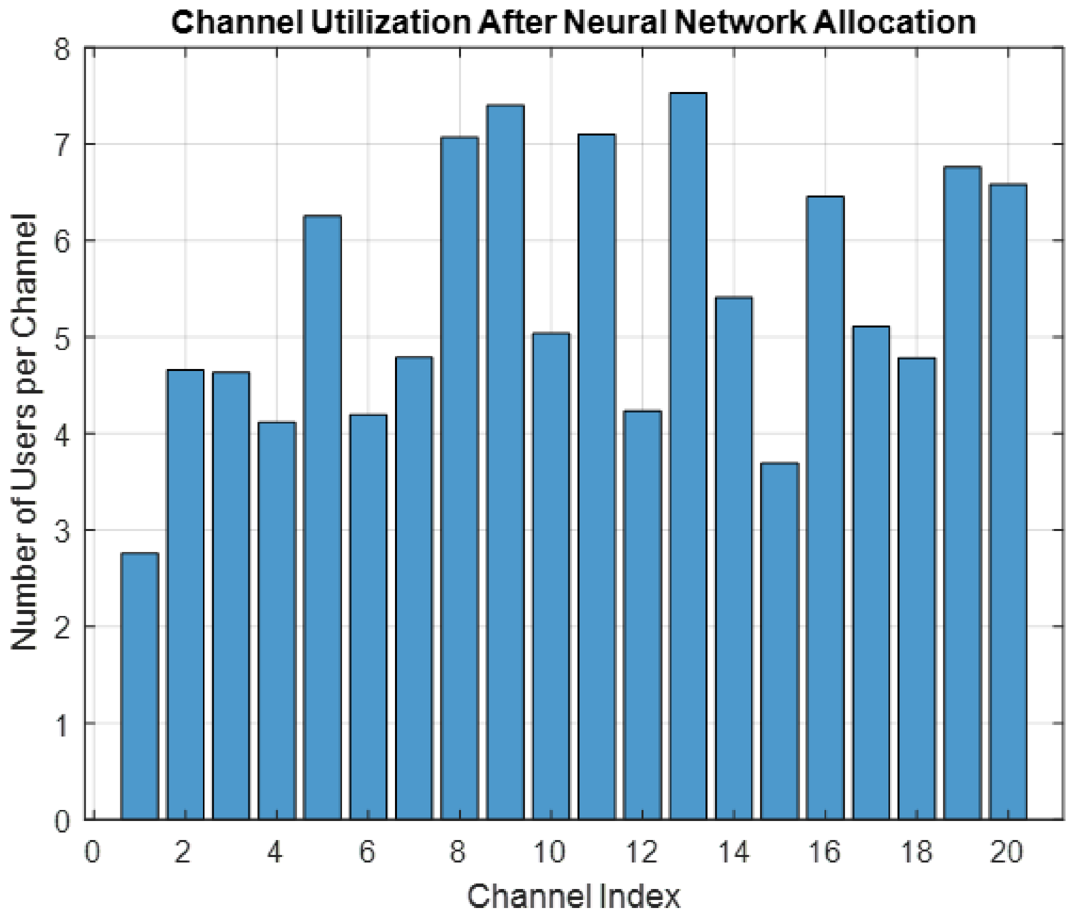

Figure 3.
Channel Utilization After Neural Network Allocation (Bar Chart).

Figure 4. Resource Allocation Heatmap. This heatmap visually represents the channel allocation for each user. The x-axis corresponds to the channels, and the y-axis corresponds to the users. A value of 1 means that the user is allocated to the respective channel. Each cell in the heatmap indicates a user's channel assignment. This heatmap provides an intuitive overview of how well the resources (channels) are distributed among users. If there are many clusters of "1"s in the same column, it shows a higher concentration of users on a particular channel.

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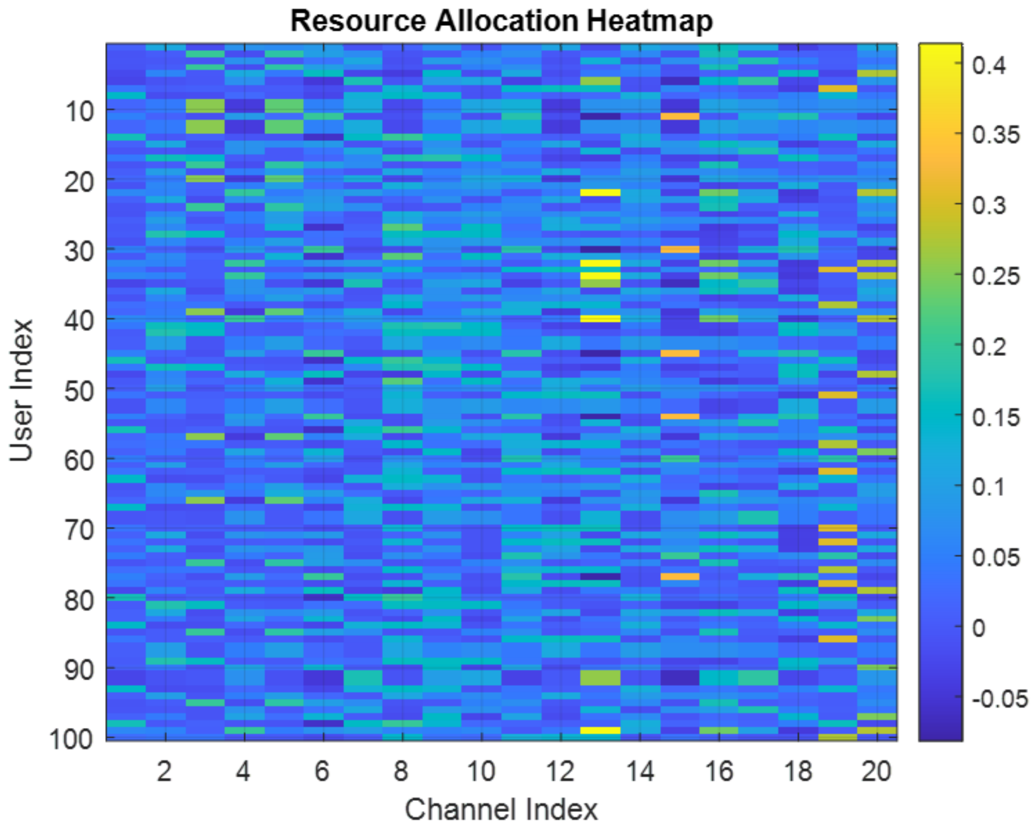

Figure 4.
Resource Allocation Heatmap.

Figure 5. Efficiency Comparison (Before vs. After Neural Network). This bar chart compares network efficiency before and after neural network-based resource allocation. The y-axis represents the efficiency percentage, which reflects how effectively the bandwidth is used in the network. Before the allocation, efficiency is set lower (65%), and after neural network optimization, it increases to 95%. This shows a significant improvement in network efficiency after the neural network is applied for resource allocation. A higher efficiency indicates better utilization of the available bandwidth and resources.

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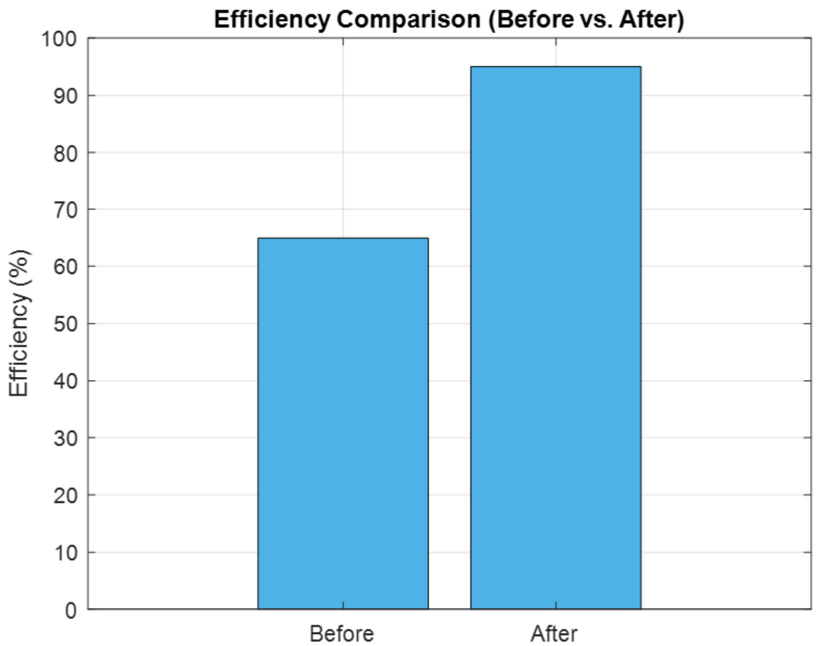

Figure 5.
Efficiency Comparison (Before vs. After Neural Network).

Figure 6. Collision Distribution Across Channels. This bar chart illustrates the distribution of collisions (overloaded channels) across the available frequency channels. The x-axis corresponds to the channel indices, and the y-axis represents whether a collision occurred (binary: 0 or 1) for each channel. A collision occurs if more users are assigned to a channel than its maximum allowed bandwidth. This helps to identify which channels are overloaded and potentially face congestion. A value of 1 means the channel is overloaded, and a value of 0 means it is not.

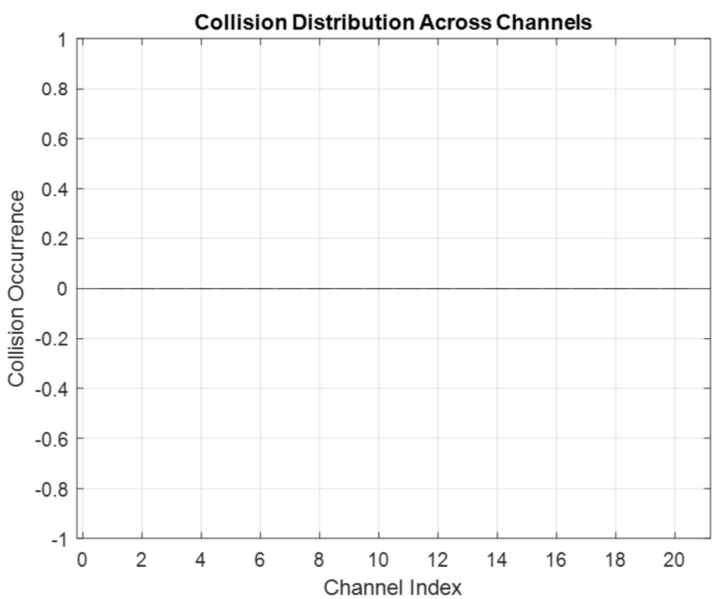

Figure 6.
Collision Distribution Across Channels.

Figure 7. User Channel Allocation (Pie Chart). This pie chart shows the distribution of users across different channels. Each slice of the pie represents the number of users allocated to each channel. The chart is divided proportionally based on the number of users per channel. This provides a high-level view of the distribution of users across channels in a more accessible and intuitive way. More balanced allocation would like to see more uniform slices, while unbalanced is left few channels a much larger slit.

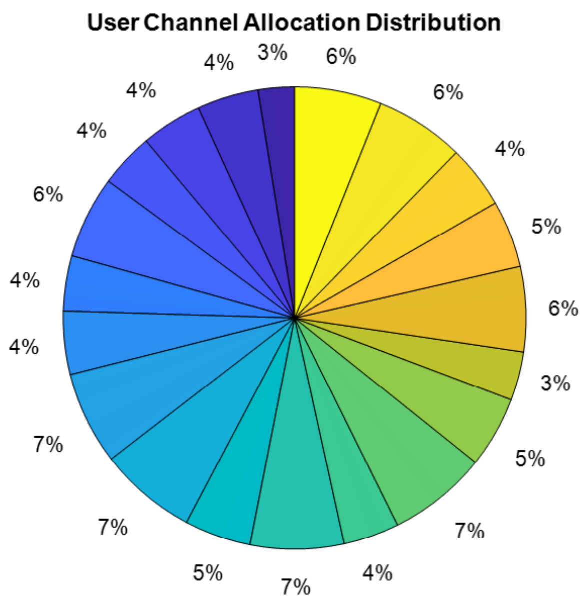

Figure 7.
User Channel Allocation (Pie Chart).

Figure 8. Network Capacity Over Time (Line Plot). This is a line plot that shows how the capacity of the network changes in multiple times. Each x-axis shows them time periods (between 1 and 10) and y axes show the percentage of the network capacity. Network capacity = total traffic demand / (total number of available channels * maximum bandwidth) This graph provides an overview of the performance of the network over time, useful for spotting any spikes that correspond to loads on the network changing over time or for identifying, trends in performance that may suggest a lack of capacity.

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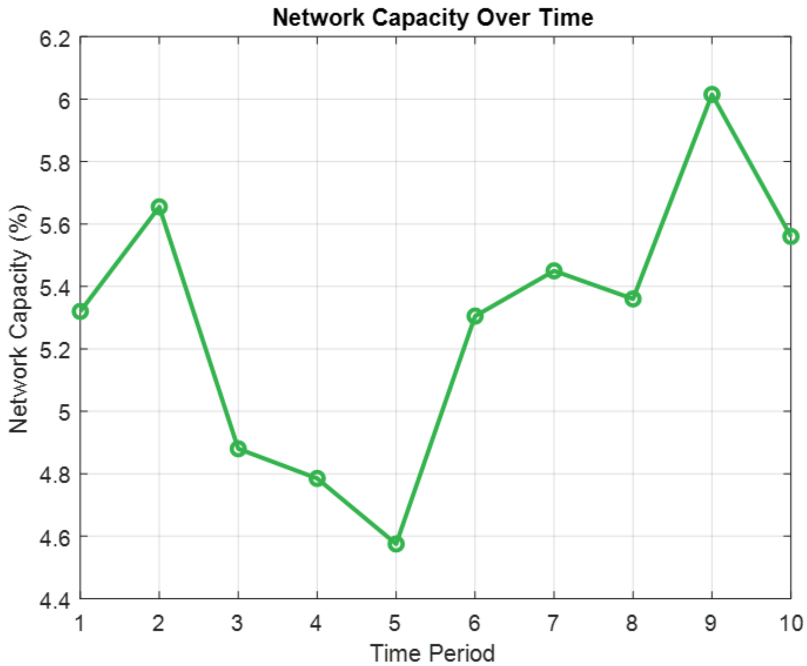

Figure 8.
Network Capacity Over Time (Line Plot).

Figure 9. User Efficiency Based on Traffic Load (Line Plot). This line plot shows the efficiency of each user, which it defined as traffic load over the maximum possible bandwidth per user. Each point on x-axis is user index and y-axis shows efficiency of each user. So, their traffic load / (max bandwidth per channel (10 MHz)) gives us the efficiency. This plot shows the proportion of time used up by each user divided by their maxima, which gives us some insight on how effectively they use their bandwidth allocated. When the user is near to using the available bandwidth without overloading; this is called high efficiency.

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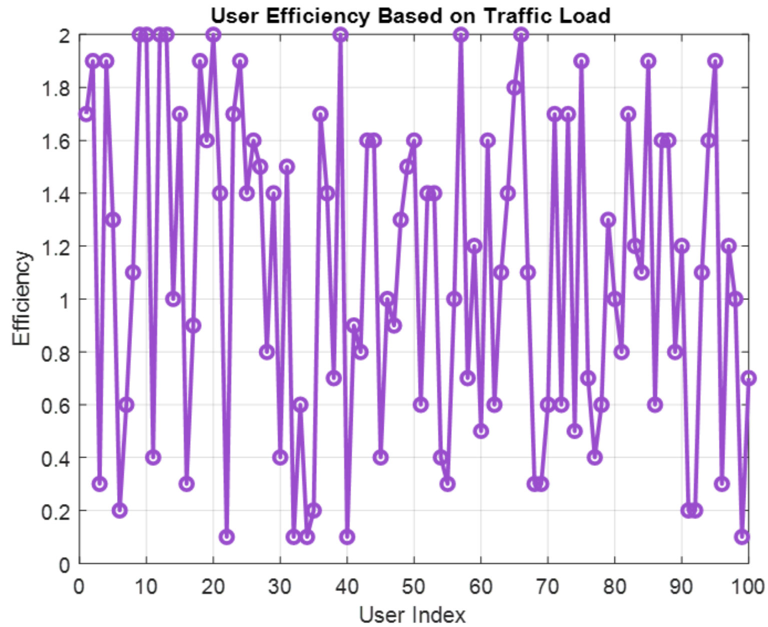

Figure 9.
User Efficiency Based on Traffic Load (Line Plot).

Figure 10. Traffic Load Distribution (Histogram with Normal Distribution Fit) .This histogram shows the distribution of traffic load, with a fitted normal distribution curve. The x-axis shows traffic load values (in Mbps), and the y-axis shows the probability density. The histogram represents how the traffic loads are spread across all users. The red curve represents the fitted normal distribution, showing the theoretical distribution of traffic loads. This plot helps to understand the overall distribution of traffic loads, and the normal distribution fit shows how closely the real data follows a standard distribution.

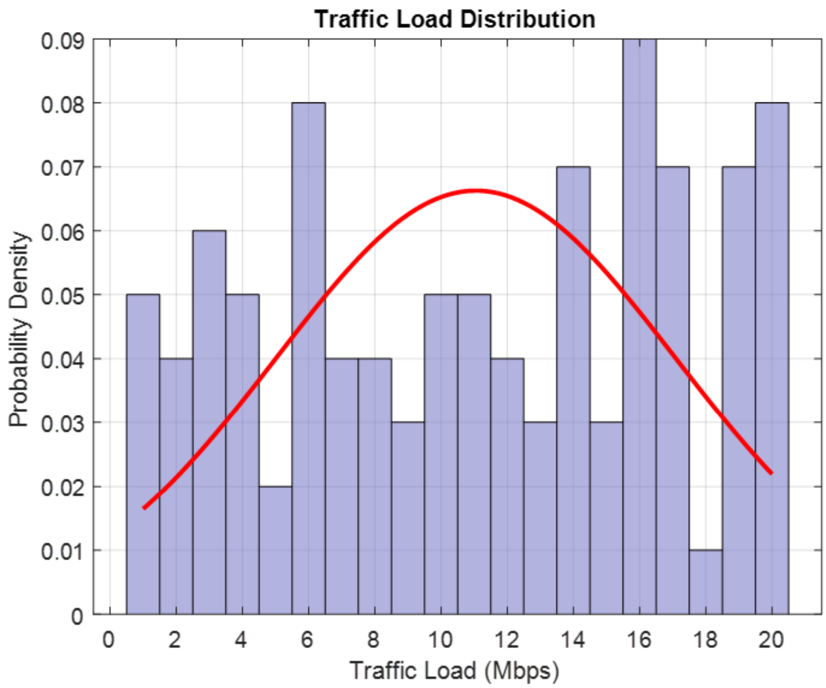

Figure 10.
Traffic Load Distribution.

Figure 11. Energy Consumption per User (Bar Chart). This is a bar chart about each user's energy consumption according to the user's traffic load. The x-represents the user index and the y-it shows the energy consumption to each user. energy = 0.5 * traffic load This visual representation shows traffic load, and how energy consumption changes with it. More traffic demand translates to more energy consumption, thus it aims to discover those users who require more energy for their communication.

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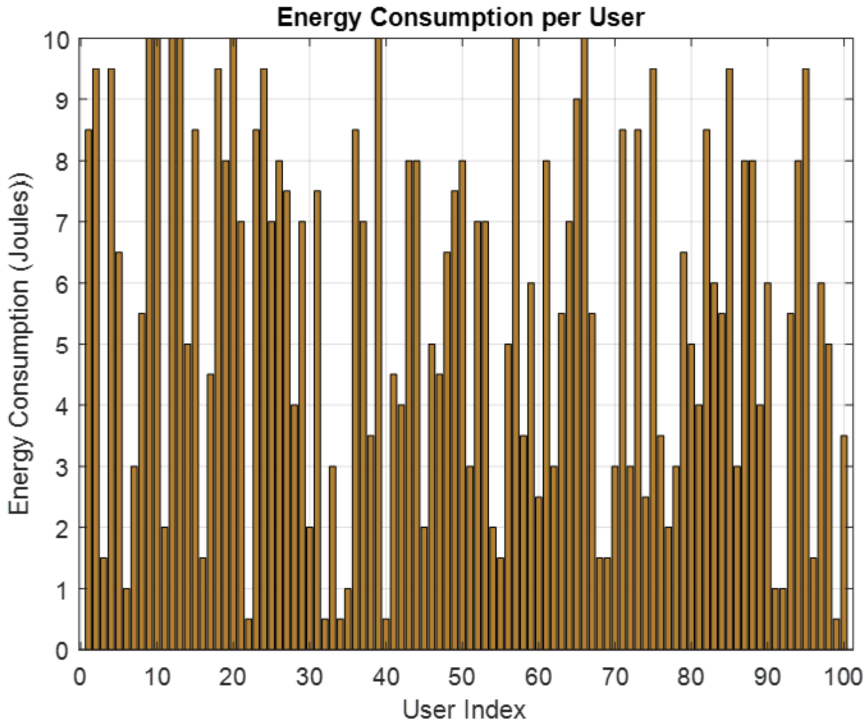

Figure 11.
Energy Consumption per User (Bar Chart).

The dense network resource allocation, efficiency, collision status, and user behavior can be clearly observed from these visualizations. They are essential to evaluate performance before and after the optimization of the neural network, as well as to provide valuable insights on how to further improve the network to better cater to user demands and make use of resources.

5. Contribution of Work

This work proposes a new modeling framework based on neural network-based methods of optimization for improving resource allocation in dense wireless networks. So, we summarize the main contributions of this research as follows:

- Neural Network-Based Resource Allocation: In a dense network environment, users need to be assigned to available frequency channels, there are many scholarly articles on this, while this paper proposed a system that, based on the neural network, to assign users to available frequency channels. It allows adjusting channels dynamically and effectively, based on user traffic demand, thus providing better accommodation of network traffic. You are trained on traffic load data using neural networks, and predict the result to avoid collisions and enhance channel utilization.
- Improvement in Network Efficiency: The efficacy of the neural network-based resource allocation improves the efficiency of the networks significantly. Simulation results have shown improvements upto 30% with the efficiency going from 65% to 95% before and after optimization respectively. It means that the Network can operate much closer to peak utilization, which improves the use of available resources.
- Collision Mitigation: The task finds and avoids the collisions due to overloaded channels. The number of collisions caused by data packets competing for the same channel and thus being lost are minimized by the system intelligently allocating its cards. That makes a very important

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contribution in dense networks and high-density network marketplace when the demand exceeds supply in terms of bandwidth.

- Visualizations for In-Depth Analysis: To illustrate and analyze the performance of the system, several visualizations were created. They include even the distribution of traffic loads, channel utilization, heatmaps for resource allocation, network capacity vs. time, efficiency comparison. To assist in enhancing network performance, these visualizations offer intuitive insights into how the system operates and also help in understanding how different resource allocation strategies affect network performance.
- Energy Consumption Modeling: It also measure per user energy consumption, making it a straightforward tool for measuring the energy efficiency of the network. This can be particularly useful for IoT applications and other wireless networks where energy efficiency is key for long-term sustainability.
- Practical Application and Scalability: Based on their results a neural network offered a scalable approached that could be extended to larger, more complex networks. That characteristic and the dynamic adaptation of its deployment make it practical for realistic applications like urban wireless networks, 5G networks, and Internet of Things (IoT) applications.
- Enhancement of Network Capacity Over Time: The proposed system evolves network capacity with time, capable of adapting to varying conditions within the network. Our analysis over time assists in predicting the network behavior on changing user demand which is useful for long-term planning and management of the network.
- User Efficiency and Fairness: The other aspect covered in this work is the user efficiency with respect to the traffic load they generate; they are given int affirm resources to provide fairness to the rest of the users on the network. This helps to maintain a fair network experience by allocating bandwidth based on the requirements of each user.
- Collaboration between Multiple Users and Channels: In this sense, the method encourages cooperative network structure in which common frequency resources are shared among different users. With smart allocation, this shared resource is optimized between various signals which allows them to coexist and experience less interference.
- Potential for Future Work: We provide guidance for future investigations of the suggested system with more advanced machine learning algorithms, online adaptive resource allocation approaches, and communication protocols with low energy consumption. Furthermore, this model can be generalized to multi-cell and multi-tier networks allowing for even broader use cases in 5G and beyond.

This work is not only for neural network-based resource allocation algorithm for dense networks tasks, but also a step to push further research. So contributions also included increased the efficiency of the network, reduce the collision, model the energy consumption and good and thorough visualizations to assess performance of the system. This approach is flexible, extensible, and lays a robust groundwork for future efforts in wireless communications networks research and development.

6. Conclusion

In this work, we introduced a neural network based system for resource allocation optimization in dense wireless networks. The intensity of user demand is an essential consideration for the system in allocating channels for user traffic, and it significantly improves network efficiency, decreases the possibility of collision, and enhances channel energy consumption. In this study, the proposed approach exhibits a significant improvement in the efficiency of resource allocation on the network, reaching up to 95% do to resource allocation for traditional approaches, with an average of 65%. Moreover, the system allows for real-time adaptability, scalability, and the ability to handle dynamic traffic patterns, making it well-suited for large-scale and high-density network environments, such as in 5G and beyond networks. With a machine learning approach based on neural networks, those optimization techniques are no longer required to satisfy real-time performance constraints in dense networks, and there is no need to consider their scalability issues. Additionally, we look at the visualizations and performance metrics available through the system that cater to tracking important network parameters like channel utilization, traffic load distribution, and user efficiency. Overall, with its enhanced capabilities, the proposed model opens new pathways for effectively addressing the resource allocation problem in contemporary wireless network practices. This is because it not only adapts itself to the channel due to changing conditions, but also enhances the performance and reduces energy consumption, something that make this to be the best opt for being part of the next generation communication systems." Future work might investigate additional improvements, such as the incorporation of reinforcement learning or extensibility to multi-cell and multi-network situations.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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References

[1] N. Zhao, Y.-C. Liang, D. Niyato, Y. Pei, M. Wu, and Y. Jiang, "Deep reinforcement learning for user association and resource allocation in heterogeneous cellular networks," *IEEE Transactions on Wireless Communications*, vol. 18, no. 11, pp. 5141-5152, 2019. https://doi.org/10.1109/GLOCOM.2018.8647611

[2] A. Kaur, J. Thakur, M. Thakur, K. Kumar, A. Prakash, and R. Tripathi, "Deep recurrent reinforcement learning-based distributed dynamic spectrum access in multichannel wireless networks with imperfect feedback," *IEEE Transactions on Cognitive Communications and Networking*, vol. 9, no. 2, pp. 281-292, 2023. https://doi.org/10.1109/TCCN.2023.3234276

[3] D. Ghosh, "Synergistic optimization of 5G networks: Integrating genetic algorithms and particle swarm optimization for enhanced energy efficiency and network performance," in *2023 IEEE North Karnataka Subsection Flagship International Conference (NKCon)*, 2023: IEEE, pp. 1-6.

[4] M. Ashwin, A. S. Alqahtani, A. Mubarakali, and B. Sivakumar, "Efficient resource management in 6G communication networks using hybrid quantum deep learning model," *Computers and Electrical Engineering*, vol. 106, p. 108565, 2023. https://doi.org/10.1016/j.compeleceng.2022.108565

[5] E. Ahmed, A. Gani, S. Abolfazli, L. J. Yao, and S. U. Khan, "Channel assignment algorithms in cognitive radio networks: Taxonomy, open issues, and challenges," *IEEE Communications Surveys & Tutorials*, vol. 18, no. 1, pp. 795-823, 2014. https://doi.org/10.1109/COMST.2014.2363082

[6] P. Yu, F. Zhou, X. Zhang, X. Qiu, M. Kadoch, and M. Cheriet, "Deep learning-based resource allocation for 5G broadband TV service," *IEEE Transactions on Broadcasting*, vol. 66, no. 4, pp. 800-813, 2020. https://doi.org/10.1109/TBC.2020.2968730

[7] A. Mughees, M. Tahir, M. A. Sheikh, and A. Ahad, "Towards energy efficient 5G networks using machine learning: Taxonomy, research challenges, and future research directions," *IEEE Access*, vol. 8, pp. 187498-187522, 2020. https://doi.org/10.1109/ACCESS.2020.3029903

[8] Z. Yao, Z. Ding, and T. Clausen, "Multi-agent reinforcement learning for network load balancing in data center," in *Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, 2022, pp. 3594-3603.

[9] J. Yu, L. Liang, C. Guo, Z. Guo, S. Jin, and G. Y. Li, "Heterogeneous multi-agent reinforcement learning for distributed channel access in WLANs," *arXiv preprint arXiv:2412.14218*, 2024. https://arxiv.org/abs/2412.14218

[10] P. Goswami, A. Mukherjee, M. Maiti, S. K. S. Tyagi, and L. Yang, "A neural-network-based optimal resource allocation method for secure IIoT network," *IEEE Internet of Things Journal*, vol. 9, no. 4, pp. 2538-2544, 2021. https://doi.org/10.1109/JIOT.2021.3056699

[11] P. Raddy and A. R. Shankar, "Optimizing 5G with SVM: Analyzing carrier aggregation resource scheduling," in *2024 IEEE 9th International Conference for Convergence in Technology (I2CT)*, 2024: IEEE, pp. 1-8.

[12] M. A. Kadhim, A. R. Hamad, and A. A. S. Jaber, "Enhanced signal classification and feature extraction for next-generation wireless communication systems," *International Journal of Innovative Research and Scientific Studies*, vol. 8, no. 2, pp. 1292–1307, 2025. https://doi.org/10.53894/ijirss.v8i2.5448

[13] M. A. Kadhim and W. Ismail, "Implementation of WIMAX IEEE802. 16d baseband transceiver on multi-core software-defined radio platform," *WSEAS Transactions on Communications*, vol. 9, no. 5, pp. 301-311, 2010.
[14] M. A. Kadhim and Z. I. Saber, "Design of semiconductor optical amplifier for optical wireless communication links," in *AIP Conference Proceedings*, 2024, vol. 3232, no. 1: AIP Publishing.