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Enhancing Next-Generation Wireless Communication Networks Through AI-Driven Resource Allocation and Intelligent Spectrum Management

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ABSTRACT

Next generation wireless communication networks require intelligent mechanisms to support high data rates, massive connectivity, low latency and efficient resource utilization. In dynamic 5G, beyond 5G and emerging 6G scenarios, traditional resource allocation and spectrum management techniques usually encounter challenges. In this paper, we propose an AI-based approach for QoS prediction and intelligent bandwidth/spectrum resource management based on 5G resource allocation dataset. The methodology consisted of data pre-processing, removal of duplicates, prevention of leakage, feature engineering, model training, validation and simulation-based resource-allocation analysis. We tried out different regression models like Linear Regression, Ridge, Lasso, Decision Tree, Random Forest, Extra Trees, Gradient Boosting and MLP Regressor. The tuned Random Forest had the best performance with R2, MAE and RMSE of 0.8954, 0.6204 and 0.9250 on the independent test dataset. The feature-importance analysis showed that resource_density was the most important predictor, i.e., the combination of CPU and available bandwidth per user is a strong determinant of QoS. Simulation results also indicated that QoS decreases with increasing user density, necessitating adaptive monitoring and dynamic resource management. The study concludes that QoS-aware resource planning in next-generation wireless networks can be aided by AI-based prediction.

Keywords: Artificial Intelligence; Resource Allocation; Spectrum Management; Quality of Service; 6G Wireless Networks

INTRODUCTION

Next-generation wireless communication networks are under rapid transformation to address the needs of the high data rate, large connectivity, low latency, and efficient service delivery. Beyond 5G and 6G is driving 5G networks to become adaptive, data-driven systems. Artificial Intelligence (AI) is a critical factor, helping to make intelligent decisions on all layers of the network, such as in resource allocation and mobility management. Traditional methods are unable to meet the complexity and dynamic characteristics of future wireless networks, making AI-driven approaches crucial for 6G networks [1].

The two most important functions in wireless networks are resource allocation and spectrum management, which directly impact on the throughput, latency, interference, fairness, energy use and quality of service. Resource-Allocation Schemes are usually based on a fixed mathematical model, on a set of assumptions, and/or on a centralized control mechanism. But future wireless environments will be very dynamic with dense deployment of small cells, large quantities of machine to machine communication (M2M), mobile edge services, reconfigurable architectures, and a range of user requirements. In such cases, DRL has become a promising technique since wireless agents can learn optimal or near-optimal policies via interaction with the complex environment, which is applicable in dynamic spectrum access, power allocation, handover control, caching, computation offloading, and network slicing [2].

The growing body of data in the network also has motivated mobile and wireless networking researchers to leverage deep learning. Deep learning models can extract hidden patterns from massive information on traffic, channel, mobility, and interference that can be used to make more precise predictions, and more adaptive control than numerous traditional traffic models. These models are especially useful in more complicated wireless systems where exact analytical modeling is difficult and/or expensive. The applications are traffic classification, channel estimation, mobility prediction, localization, anomaly detection, congestion control and adaptive radio-resource management [3]. Artificial neural networks, likewise, are a versatile learning model for wireless-network optimization and are used to approximate the nonlinear relationship between the state of the network and control actions. They have applications in communication systems that enable intelligent prediction, classification and decision making in uncertainty and high dimensional data world [4].

While all these advances have been made, some issues have yet to be solved. The need for spectrum is still increasing with the growth of mobile broadband, the Internet of Things (IoT), industrial automation, smart cities, autonomous vehicles and immersive applications, and wireless spectrum is scarce and expensive. Congestion, interference, service degradation and poor spectral efficiency can be caused by enabling statically allocated spectrum and inefficient resource utilization. Machine learning has been recognized as a solution to these challenges, yet there are problems in implementing it such as data availability, model generalization, computational burden, model explainability, security, privacy, and real-time implementation [5]. Thus, the effect of intelligent spectrum management and resource allocation using AI on the performance of next-generation wireless networks must be explored, and practical considerations that can restrict the deployment of such techniques must be taken into account.

This research focuses on spectrum management and resource allocation techniques that are enabled by AI in next generation wireless communication networks, including 5G, beyond 5G and emerging 6G systems. The study investigates how machine learning, deep learning, and deep reinforcement learning can be applied to optimize radio resources, minimize interference, boost the spectrum efficiency, and facilitate smart management of the network. It emphasizes on conceptual, architectural and algorithmic advances rather than of hardware-level design or physical-layer circuit implementation. The study also suffers from the fact that many of the existing AI-driven wireless-network solutions are still at the simulation and prototype stages, and their performance might differ when deployed in practical environments, such as imperfect channel knowledge, limited training sets, user movement, diverse traffic, and security attacks.

The importance of this research is to help understand the potential of AI in enabling more autonomous, efficient and scalable wireless networks. With 5G heterogeneous networks becoming denser and more complicated, multiple conflicting requirements are involved in resource management, including capacity, fairness, latency, reliability and energy usage. Deep reinforcement learning (DRL) has proven promising in solving 5G heterogeneous resource-management problems since it is capable of learning the control policies for the complex optimization problems while adapting to the changing network states [6]. Moreover, in addition to the concept of 6G communication, the vision of 6G also encompasses the terms of intelligent connectivity, integrated sensing, edge intelligence, and new applications like extended reality, holographic communication, digital twins, and autonomous systems [7]. The advancements are driving the need for more intelligent resource allocation and spectrum management in wireless networks, highlighting the critical role of AI in shaping their design for the future.

Next generation wireless systems will leverage a variety of technologies including millimeter-wave and terahertz communication, massive MIMO, intelligent reflecting surfaces, cloud-native networking, and distributed edge intelligence. These technologies present new opportunities for performance improvement, but add to the complexity of network planning and control. In the future, 6G, intelligent use of communication resources will be required to deploy various services with diverse quality of service requirements, keeping spectrum efficiency and reliability high [8]. In this context, the aim of this study is:

- To examine the role of AI-driven techniques in improving resource allocation for next-generation wireless communication networks.
- To analyze how intelligent spectrum management can enhance spectral efficiency, interference control, and network adaptability.
- To identify major challenges and limitations affecting the practical deployment of AI-based resource and spectrum-management solutions in 5G, beyond-5G, and 6G networks.

2. LITERATURE REVIEW

AI is now a major enabler for resource allocation, spectrum management and self-optimizing networks for next generation wireless communication networks, as demonstrated by recent studies. Lin and Zhao investigated resource management based on AI technology for the future wireless communications system and pointed out that the traditional optimization methods may be inadequate in the highly dynamic, dense and heterogeneous network. According to their survey, the following four areas represent valuable applications of AI techniques to enhance network efficiency and adaptability in power control, user association, spectrum allocation, caching and computation offloading [9]. Based on this trend, Meng et al. explored Deep Reinforcement Learning techniques for power allocation in multi-user cellular systems. Their work proved that the reinforcement learning algorithm can optimise the power of the transmitters under complex interference conditions, without requiring full fixed mathematical models and perfect channel assumptions to have been made [10].

The problem of allocating frequencies has also been a subject of much interest in the research of wireless-networks with artificial intelligence. For integrated access and backhaul networks, spectrum resources need to be utilized efficiently between both access and backhaul links, which requires a spectrum allocation method, proposed by Lei et al., that is based on deep reinforcement learning. Their study demonstrated that DRL can be used to assist in adaptive spectrum decision making in dynamic network environment and can also be used to mitigate interference and achieve better utilization of the entire network resources [11]. Wang et al. gave a wider survey on machine learning in wireless networks and talked about the trend towards Pareto-optimal wireless networks. They highlighted the fact that future networks need to optimize several competing metrics (e.g., throughput, latency, reliability, energy efficiency, fairness) and not just a single one of them [12].

AI-based resource allocation is also connected to the overall advancement of 6G networks, as per the literature. Yang et al. spoke about the intelligent operation and intelligent provisioning of 6G networks, and suggested that AI will play a key role in ensuring autonomous operation, intelligent service provisioning and adaptive network control. Their work put AI on a pedestal as an optimization tool and as a building block of the architecture of future networks [13]. Shen et al. also explored the resource management in future wireless networks using AI, highlighting the need to leverage AI to handle complex radio-resource management problems that are challenging with traditional optimization techniques. Their analysis underlined the importance of AI for future networks in terms of improving the scalability, flexibility, and real-time decision-making [14].

The deep reinforcement learning will play an important role in the joint resource-allocation issues associated with multiple radio parameters. Nasir and Guo demonstrated the interdependency of spectrum and power allocation for DRL, and proved that it can coordinate them in various traffic and interference cases [15]. Bartsiokas et al. conducted another survey of the existing literature and research on ML for radio-resource management in 5G and beyond, including topics such as scheduling, beam management, and interference mitigation, and highlighted the associated challenges and requirements, such as the complexity of training ML models, limited information available for training, and the need for a high degree of real-time implementation [16].

One such example where machine learning can help with intelligent resource allocation is network slicing. Under different traffic load conditions, Azimi et al. presented the efficient use of the dynamic allocation of radio and computational resources across various services using ML [17]. The 5G and beyond networks also rely on spectrum sharing. Patil et al., emphasized the need for intelligent sharing mechanisms in improving the spectrum utilization in dense and heterogeneous wireless network [18].

AI-driven resource allocation has since been taken into the cloud-native, software-defined wireless networks. Wang et al. suggested a deep reinforcement learning-based method of resource allocation for cloud-native wireless networks, highlighting the importance of AI in flexible, programmable and virtualized networks. This work is important because future networks are likely to increasingly use cloud-native architectures that allow for network functions to be dynamically deployed and scaled as needed [19]. Sabir et al. performed systematic literature review at the spectrum-management level on how AI is applied to spectrum management in 6G and future networks. Their review showed that while AI can aid in spectrum sensing, access control, interference prediction, and dynamic spectrum allocation, issues with security, reliability, data quality and regulatory acceptance were also highlighted [20].

Recent literature further links AI to a variety of access and spectrum sensing for 6G systems. As regards 6G's multiple access, Zhang et al. looked at AI-assisted spectrum sensing, multiple access protocol design, and optimization. They found that AI could be used to enable better adaptive transmission strategies and learn from complex radio environments to better support massive connectivity and other more flexible access mechanisms for future networks [21]. In general, the analysed literature revealed that intelligent resource allocation and intelligent spectrum management are crucial for next generation wireless networks with the assistance of AI. The power control, spectrum sharing, RAN slicing, cloud-native networking and 6G multiple access are key areas of strong potential, as shown by existing studies. At the same time, challenges in the implementation of these systems are also persistent in the literature as are computational cost, limited training data, scalability, explainability, security and real-time deployment. These gaps call for the need of exploring practical and reliable frameworks of AI to boost the efficiency and intelligence of future wireless communication networks.

3. METHODOLOGY

3.1 Research Design

This study uses a quantitative experimental machine learning methodology to investigate AI-driven resource allocation and intelligent spectrum-resource management in next-generation wireless networks. The methodology is to create a prediction model to find the Quality of Service (QoS) based on the network resource-allocation parameters and utilize the trained prediction model to make intelligent decisions on resource allocation.

The problem is stated as a supervised regression problem, where the model is trained to learn the relationship between the resource-allocation variables and the QoS. The expected QoS is later used to support decision making with adaptive resource allocation and intelligent bandwidth/spectrum management.

3.2 Dataset Description

The study uses a 5G resource allocation dataset consisting of separate training and testing files. The original training data had 16,539 records and 6 attributes, the test data had 345 records and 6 attributes. This is a dataset that contains time, total bandwidth usage, CPU allocation, bandwidth allocation, number of users, and QoS. These variables are significant operational parameters in a wireless communication environment particularly for analyzing the impact of resources availability and user density on the service quality.

In this study the target variable chosen is the service quality level (qos) obtained under certain resource allocation circumstances. The main allocation-related variables for the model training are CPU allocation, bandwidth allocation, and user number. These parameters are important for next generation wireless systems since dynamic resource allocation in 5G/beyond-5G/6G networks is required to adapt to traffic variation, user density, and service requirements for service quality [22].

3.3 Data Preprocessing

A systematic preprocessing procedure was used prior to model training. The dataset has been checked for its structure, data types, duplicate records and blank data. Time was set to datetime format to make it consistent and put it in chronological order. The data set was cleaned by removing duplicate records, totaling 30 from the training data set, which dropped it from 16,539 to 16,509, and 345 records from the test data set.

All the numerical columns were converted to the proper numeric data types. All the data points were found to be available in the both training and test sets through the process of missing value analysis. To ensure the robustness and the repeatability of the workflow a step of median-based imputation on the training set was introduced. Both datasets were free from any preprocessing issues and were ready for machine learning experiments.

3.4 Data Leakage Prevention

A leakage verification step was carried out to make sure that the model did not learn a mathematical shortcut instead of effective resource allocation behavior. Analysis revealed that the total bandwidth usage divided by the number of users is directly derived as QoS. Thus, it would be a data leakage and artificially high model results if you use total_bandwidth_usage as an input feature.

To prevent this, bandwidth usage of the total bandwidth was not included in the model input features. The last predictive model was trained with the variables at the allocation level only and engineered features from CPU allocation, bandwidth allocation and number of users. The design can be leakage-aware to enhance the methodological validity of the experiment and target the resource-allocation patterns instead of directly reconstructing the target variable.

3.5 Feature Engineering

Feature engineering to enhance the model's sensitivity to resource availability and to relationship between user-load and resources. Four new features were derived from the allocation variables. The first, bw_per_user, is bandwidth per user who is connected. In the second one (cpu_per_user), the CPU amount allocated to each user is specified. The third feature, resource_density, is a combination of CPU and bandwidth availability, based on the number of users, and is computed as CPU times bandwidth per user. user_load_ratio is the fourth feature, which is the ratio between the number of users and the bandwidth allocated.

Seven input features were selected for the final set: cpu, bw, n_users, bw_per_user, cpu_per_user, resource_density and user_load_ratio. The features chosen reflect the direct and derived conditions of resource allocation which affect QoS in wireless communication networks.

3.6 Model Development and Training

The cleaned training dataset was then divided into 80% for training and 20% for testing, which resulted in 13,207 training records and 3,302 validation records. Various regression models were built and evaluated using multiple regression models: Linear Regression, Ridge, Lasso, Decision Tree, Random Forest, Extra Trees, Gradient Boosting, Multilayer Perceptron Regressor.

The performance of model was evaluated based on MAE, MSE, RMSE and R^2 score. The best validated model was Random Forest and it was chosen for tuning. It was optimized using a 5 fold grid search with the optimum parameters: 300 estimators, maximum depth of 10, minimum samples split of 2 and minimum samples leaf of 2.

3.7 Model Validation and Testing

The tuned Random Forest model was evaluated using hold-out validation, shuffled 5-fold cross-validation, and final test-set evaluation. The R^2 values were stable with a mean of 0.8970 and a standard deviation of 0.0026, obtained from the 5-fold cross validation method with shuffling. The model was trained with the entire cleaned training set and then tested on the independent test set.

The final test performance achieved MAE of 0.6204, MSE of 0.8557, RMSE of 0.9250, and R^2 of 0.8954. The aforementioned results suggest that the model is able to predict QoS with a very high accuracy at the allocation level using resource features.

3.8 AI-Driven Resource Allocation and Intelligent Management Simulation

The validated tuned Random Forest model was applied to simulate the AI driven Resource Allocation for 320 CPU-BW-User scenarios. The model was used to predict QoS for each scenario with the parameters CPU allocation, bandwidth allocation, and number of users.

The predicted QoS values were categorised as Low, Moderate, and High QoS levels. Low QoS scenarios suggested to increase bandwidth or CPU allocation or to decrease user load. With moderate QoS, adaptive monitoring was needed, and with High QoS, efficient allocation was found. In this simulation, the AI framework can be applied to assist intelligent spectrum-resource management and adaptive wireless network optimizing.

4. RESULTS

4.1 Model Evaluation Results

Multiple regression-based machine learning models were used for experimental evaluation of predicting the QoS from the allocation level features of the network. The models evaluated were Linear Regression, Ridge Regression, Lasso Regression, Decision Tree, Random Forest, Extra Trees, Gradient Boosting, Multilayer Perceptron Regressor and the hyperoptimized Random Forest model. The evaluation measures used were the Mean Absolute Error (MAE), the Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and R^2 score.

The validation result of the tuned Random Forest model was the best with an MAE of 0.6988, an RMSE of 1.2113 and R^2 score of 0.8920 as presented in Table 1. Almost comparable results were obtained by the other classifiers such as Random Forest, Decision Tree, Extra Trees and MLP Regressor, while the linear models obtained relatively lower R^2 values of about 0.7445. This shows that the nonlinear models gave better performance in terms of QoS prediction with resource-allocation conditions.

Table 1. Validation performance comparison of machine learning models

Model	MAE	MSE	RMSE	R^2
Tuned Random Forest	0.6988	1.4674	1.2113	0.8920
Random Forest	0.6988	1.4676	1.2115	0.8920
Decision Tree	0.6986	1.4682	1.2117	0.8920
Extra Trees	0.6986	1.4682	1.2117	0.8920
MLP Regressor	0.7175	1.4697	1.2123	0.8919
Gradient Boosting	0.7223	1.4960	1.2231	0.8899
Lasso Regression	1.3579	3.4731	1.8636	0.7445
Ridge Regression	1.3578	3.4732	1.8637	0.7445
Linear Regression	1.3577	3.4732	1.8637	0.7445

The validation R^2 comparison of all trained models is presented in Figure 1 and it is found that the tuned RF model has the maximum validation score among all the models evaluated.

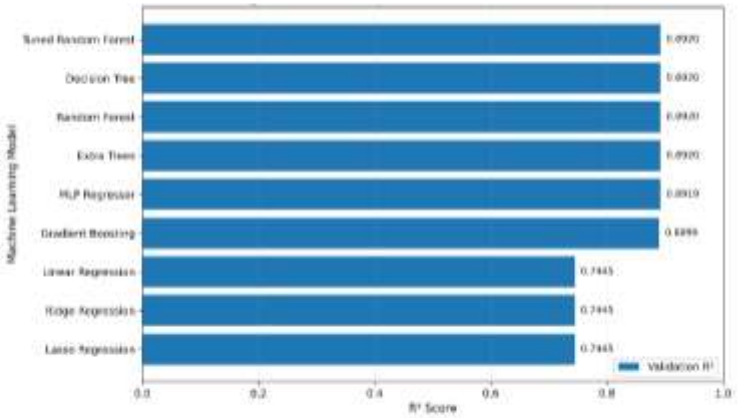

Figure 1. Model comparison based on validation R^2 score.

4.2 Final Test Result of the Selected Model

The validated and hyper-parameter optimized Random Forest model was finally considered as the predictive model. The model was trained using the complete cleaned training set and tested using the independent test set. The final test result is shown in Table 2.

Table 2. Final test performance of the tuned Random Forest model

Model	MAE	MSE	RMSE	R^2
Final Tuned Random Forest	0.6204	0.8557	0.9250	0.8954

The model performance is verified by the final test result, where the model has an R2 of 0.8954, indicating that the model can explain 89.54% of the variation of the QoS in the test data. The prediction error was also low on unseen data as demonstrated by the MAE of 0.6204 and the RMSE of 0.9250. These values indicate that the trained model's predictive abilities remained high outside of the validation subset.
The actual and predicted QoS values for the final tuned Random Forest model are shown in Figure 2 on the test set. The modeled points are mostly on the trend of the ideal prediction line, which validates the model to be capturing the primary prediction pattern of QoS.

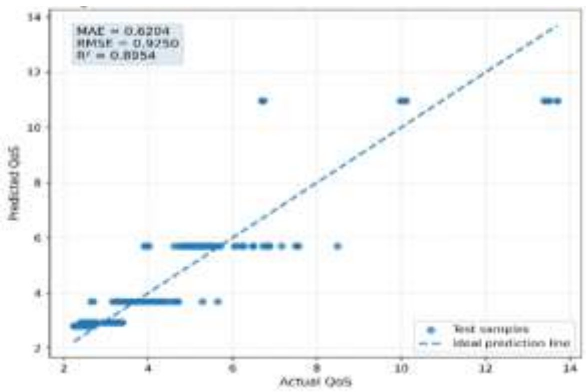

Figure 2. Actual versus predicted QoS values for the final tuned Random Forest model.

4.3 Cross-Validation Result

To verify the stability of the selected model, shuffled 5-fold cross-validation was performed. Table 3 shows the result. The mean R^2 value for the tuned Random Forest was 0.8970 with a standard deviation of 0.0026. The smallest R^2 was 0.8920 and the largest R^2 was 0.8996.

Table 3. Shuffled K-Fold cross-validation summary

Model	Cross-validation method	Mean R^2	Std. R^2	Min. R^2	Max. R^2
Final Tuned Random Forest	5-Fold Shuffled K-Fold	0.8970	0.0026	0.8920	0.8996

The small standard deviation indicates a uniformity of the performance of the selected model across the shuffled folds. All three values of R^2 (validation, cross validation, and final test) are close, suggesting that the model was not developed using one good data partition.

4.4 Feature Importance Result

The feature-importance result of the final tuned Random Forest model is presented in Table 4. Among all input variables, resource_density achieved the highest importance score of 0.913856, corresponding to 91.39% of total feature importance. The next most important features were cpu_per_user, n_users, user_load_ratio, and bw_per_user.

Table 4. Feature importance of the final tuned Random Forest model

Feature	Importance	Importance (%)
resource_density	0.913856	91.39
cpu_per_user	0.023496	2.35
n_users	0.022701	2.27
user_load_ratio	0.019544	1.95
bw_per_user	0.017182	1.72
bw	0.002090	0.21
cpu	0.001130	0.11

Figure 3 shows the feature-importance ranking of the final tuned Random Forest model and visually confirms the dominant contribution of resource_density in QoS prediction.

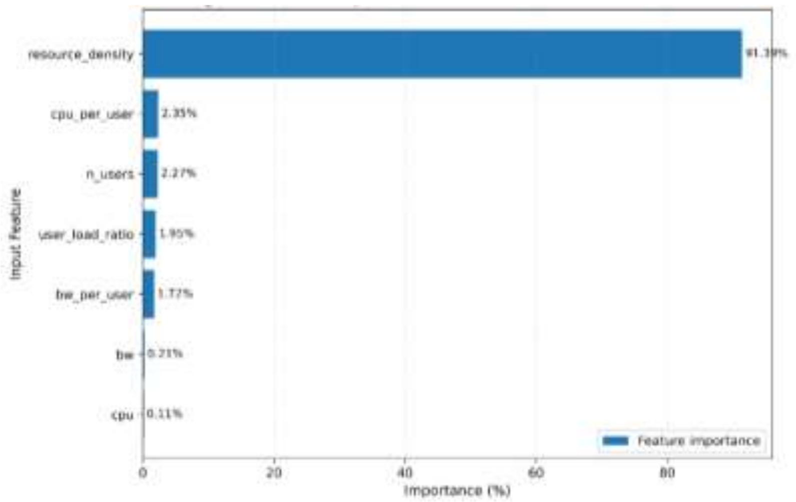

Figure 3. Feature importance analysis of the final tuned Random Forest model.

4.5 Error Analysis by Number of Users

The final test predictions were further analyzed by grouping the results according to the number of users. Table 5 reports the mean actual QoS, mean predicted QoS, MAE, MSE, and RMSE for each user group. The highest error occurred in the single-user scenario, where MAE was 1.3932 and RMSE was 1.7472. The error decreased as the number of users increased. For five users, the model achieved an MAE of 0.2864 and RMSE of 0.3044.

Table 5. Error analysis by number of users

Number of users	Sample count	Mean actual QoS	Mean predicted QoS	MAE	MSE	RMSE
1	66	10.1863	10.9568	1.3932	3.0527	1.7472
2	70	5.5877	5.6960	0.7484	0.8418	0.9175
3	73	3.8990	3.6831	0.4086	0.2951	0.5432
4	67	3.0147	2.9252	0.2999	0.1024	0.3200
5	69	2.5158	2.8022	0.2864	0.0927	0.3044

The grouped error result shows that the model predicted QoS more accurately for higher user-count groups. The single-user group produced the largest prediction error because the actual QoS values showed wider variation under the same allocation settings.

4.6 AI-Driven Resource Allocation Result

After model testing, the final tuned Random Forest model was used to simulate AI-driven resource allocation. A total of 320 resource-allocation scenarios were generated using different combinations of CPU allocation, bandwidth allocation, and number of users. The predicted QoS values ranged from 0.8324 to 11.8124, with a mean predicted QoS of 5.1393.

The model identified the best resource-allocation configuration for each user group. For one user, the best predicted QoS was 11.8124 at CPU allocation of 3000 and bandwidth allocation of 25. For two users, the best allocation was CPU 3000 and bandwidth 40, producing predicted QoS of 11.7580. For three users, the

model recommended CPU 4000 and bandwidth 40, producing predicted QoS of 10.4534. For four and five users, CPU 4000 and bandwidth 40 remained the best allocation, but the predicted QoS values decreased to 7.8201 and 6.2683, respectively.
Figure 4 presents the predicted QoS heatmap for CPU and bandwidth allocation under a three-user scenario. The heatmap shows that QoS generally increased as both CPU and bandwidth allocation increased, with the highest QoS region appearing at higher CPU and bandwidth combinations.

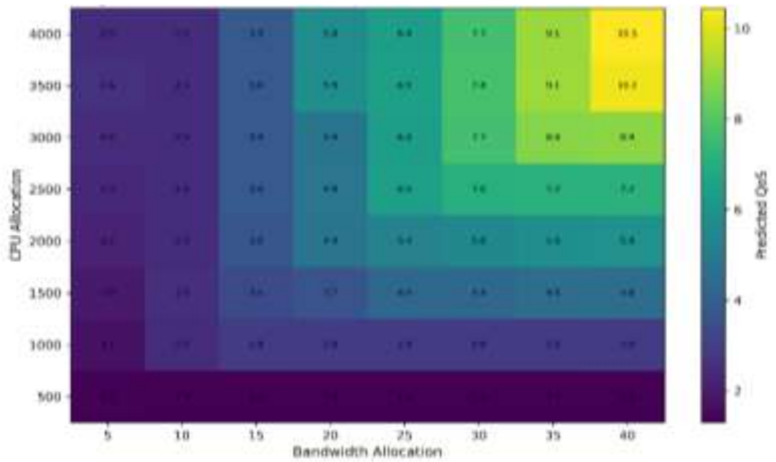

Figure 4. Predicted QoS heatmap for CPU and bandwidth allocation under a three-user scenario.

The simulated allocation results also classified 153 scenarios as Low QoS, 104 scenarios as Moderate QoS, and 63 scenarios as High QoS. The results shows that, not only can the trained model be utilized for predicting QoS, it is also used to identify the conditions under which allocation of resources needs to be adjusted, adaptively monitored or efficiently maintained.

DISCUSSION

The findings of this research indicate that the use of AI-driven resource allocation is a reliable approach for the prediction of QoS in next-generation wireless communication networks. The last tuned Random Forest model performed well with R^2 of 0.8954, MAE of 0.6204 and RMSE of 0.9250 on the independent test set. This means that the chosen allocation-level features were successful in capturing the behaviour of the QoS. The validation R^2 value of 0.8920, the shuffled cross-validation mean R^2 value of 0.8970 and the final test R^2 value of 0.8954 further confirms the stability of the model and absence of dependence on any single favorable data partition. These results give further credence to the notion that nonlinear AI models are appropriate for wireless resource-management problems that depend on interacting factors like bandwidth allocation, CPU allocation, and number of active users that affect the QoS.
The results indicate that the nonlinear model performed better than the linear ones. Linear Regression, Ridge, and Lasso had R^2 values that were approximately 0.7445 while others like Random Forest, Decision Tree, Extra Trees, MLP and Gradient Boosting were close to 0.89. This means that the relationship between the allocation of resources and the QoS is nonlinear. The outcome is consistent with previous research which showed the complexity of the wireless-network optimization problem. Letaief et al. [1] pointed out that adaptability is crucial for 6G networks and Wang et al. [12] noted the necessity of finding a trade-off between various performance metrics. These results show the effectiveness of the nonlinear models in predicting the QoS.
The result of feature importance gives an important interpretation of the model behaviour. The engineered feature resource_density is the most prominent feature and accounted for 91.39% of the importance of the features, which is the most important feature that influences the prediction of QoS. The result suggests that the aggregate of CPU and bandwidth per user is a bigger factor determining QoS than either CPU or bandwidth per user alone. The practical implication is that it may not be enough to just add additional resource; the allocation of the resources needs to be taken into account along with the load on the network. This is in line with the research of intelligent resource management in which AI-related techniques are applied to capture complex relationships between network-state variables and allocation decisions. It also corroborates the growing concept of the importance of feature engineering in the application of machine learning to the wireless-network domain, particularly when physical-layer features like channel gain, interference and/or SINR are not available directly.
The simulation using AI shows the applicability of the proposed approach. The model simulated 320 CPU-bandwidth-user scenarios, and determined the optimal allocation of CPU/bandwidth to each user group. Even with increased resource allocation, QoS decreased with increased users which further highlights the effect of user density on QoS. For example, when one user is using the system, the QoS is 11.8124, but when

five users use the system, the QoS is 6.2683. The heatmap analysis also revealed that CPU and bandwidth are positively correlated with QoS in general. The results are well aligned with the previous studies, from which Lei et al. [11] showed the adaptive decission of the spectrum through deep reinforcement learning and Sabir et al. [20] emphasized the use of AI in improving the spectrum management and allocation.

The findings of this study are applicable to the design of the next generation wireless network. The proposed model can be applied as a decision supporting tool for predicting the QoS prior to applying resource-allocation configuration. Network operators would be able to identify allocation scenarios as Low, Moderate and High QoS and determine if more resources are needed, if allocation needs to be monitored or if the current allocation configuration could be kept. This will facilitate more intelligent and adaptive management of bandwidth/spectrum resources, especially in 5G, beyond 5G and emerging 6G systems. It also shows that AI prediction can contribute to minimizing reliance on static allocation rules and can aid in data-driven network management.

However, the study has limitations. First, the dataset does not include direct physical-layer spectrum features such as SINR, SNR, channel gain, frequency band, interference level, or modulation type. Therefore, the spectrum-management component is represented through bandwidth allocation and QoS-based decision support rather than full RF-spectrum sensing. Second, total_bandwidth_usage was excluded to prevent data leakage because QoS was directly derived from it. Although this improved methodological validity, it also limited the model's ability to capture traffic-output fluctuations under identical allocation conditions. Third, the test dataset contained fixed CPU and bandwidth values, which limits the diversity of final test evaluation.

Future research should extend this work by using richer wireless datasets containing channel-state information, interference measurements, mobility patterns, traffic classes, and spectrum-occupancy indicators. Future models could also be designed to use deep reinforcement learning to make optimal allocations in a sequential manner, not just based on a static scenario and QoS predictions. Furthermore, the use of explainable AI techniques needs to be explored to enhance model transparency and trust in deployment. Lastly, further research is needed to validate the framework with real-time network traces or simulation tools that more accurately capture real-world 5G-Advanced and 6G networks.

CONCLUSION

This study examined how AI-driven resource allocation can enhance QoS prediction and support intelligent bandwidth/spectrum-resource management in next-generation wireless communication networks. The leakage-aware preprocessing and feature engineering techniques were used to assess several regression models using a 5G resource allocation dataset. The tuned Random Forest model gave the best performance with the highest R2 value of 0.8954, the lowest MAE value of 0.6204 and RMSE of 0.9250 on the independent testing set. The results demonstrate the ability of the nonlinear AI models to learn more complex relationship between CPU allocation, bandwidth allocation, user load and QoS than the linear models. A combined resource availability per user, defined through resource_density, was also identified as having a significant impact on the service quality and was confirmed by feature-importance analysis. The simulation results also demonstrated that with an increased number of users the QoS decreases even with higher resource allocation, which brings the need for adaptive monitoring and adaptive management. These results suggest that AI prediction tools can help network operators to choose efficient allocation configurations prior to deployment. Thus, future wireless systems must be equipped with modules to support the decisions at design time for QoS-aware resource planning using Artificial Intelligence. Further research is required to utilize more comprehensive data sets that include SINR, channel state, interference, mobility and spectrum-occupancy characteristics, and to investigate deep reinforcement learning for sequential resource and spectrum optimization in real-time.

REFERENCES

1. K. B. Letaief, W. Chen, Y. Shi, J. Zhang, and Y.-J. A. Zhang, "The roadmap to 6G: AI empowered wireless networks," IEEE Communications Magazine, vol. 57, no. 8, pp. 84–90, Aug. 2019.
2. Z. Xiong, Y. Zhang, D. Niyato, R. Deng, P. Wang, and L.-C. Wang, "Deep reinforcement learning for mobile 5G and beyond: Fundamentals, applications, and challenges," IEEE Vehicular Technology Magazine, vol. 14, no. 2, pp. 44–52, Jun. 2019.
3. C. Zhang, P. Patras, and H. Haddadi, "Deep learning in mobile and wireless networking: A survey," IEEE Communications Surveys & Tutorials, vol. 21, no. 3, pp. 2224–2287, 2019.
4. M. Chen, U. Challita, W. Saad, C. Yin, and M. Debbah, "Artificial neural networks-based machine learning for wireless networks: A tutorial," IEEE Communications Surveys & Tutorials, vol. 21, no. 4, pp. 3039–3071, 2019.
5. Y. Sun, M. Peng, Y. Zhou, Y. Huang, and S. Mao, "Application of machine learning in wireless networks: Key techniques and open issues," IEEE Communications Surveys & Tutorials, vol. 21, no. 4, pp. 3072–3108, 2019.

6. Y. L. Lee, D. Qin, L.-C. Wang, and G. H. Sim, "A survey on applications of deep reinforcement learning in resource management for 5G heterogeneous networks," in Proc. Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC), 2019, pp. 1856–1862.
7. W. Saad, M. Bennis, and M. Chen, "A vision of 6G wireless systems: Applications, trends, technologies, and open research problems," IEEE Network, vol. 34, no. 3, pp. 134–142, May/Jun. 2020.
8. M. Giordani, M. Polese, M. Mezzavilla, S. Rangan, and M. Zorzi, "Toward 6G networks: Use cases and technologies," IEEE Communications Magazine, vol. 58, no. 3, pp. 55–61, Mar. 2020.
9. M. Lin and Y. Zhao, "Artificial intelligence-empowered resource management for future wireless communications: A survey," China Communications, vol. 17, no. 3, pp. 58–77, Mar. 2020.
10. F. Meng, P. Chen, L. Wu, and J. Cheng, "Power allocation in multi-user cellular networks: Deep reinforcement learning approaches," IEEE Transactions on Wireless Communications, vol. 19, no. 10, pp. 6255–6267, Oct. 2020.
11. W. Lei, Y. Ye, and M. Xiao, "Deep reinforcement learning-based spectrum allocation in integrated access and backhaul networks," IEEE Transactions on Cognitive Communications and Networking, vol. 6, no. 3, pp. 970–983, Sep. 2020.
12. J. Wang, C. Jiang, H. Zhang, Y. Ren, K.-C. Chen, and L. Hanzo, "Thirty years of machine learning: The road to Pareto-optimal wireless networks," IEEE Communications Surveys & Tutorials, vol. 22, no. 3, pp. 1472–1514, 2020.
13. H. Yang, A. Alphones, Z. Xiong, D. Niyato, J. Zhao, and K. Wu, "Artificial-intelligence-enabled intelligent 6G networks," IEEE Network, vol. 34, no. 6, pp. 272–280, Nov./Dec. 2020.
14. Y. Shen, J. Zhang, S. H. Song, and K. B. Letaief, "AI empowered resource management for future wireless networks," in Proc. IEEE International Mediterranean Conference on Communications and Networking (MeditCom), 2021.
15. Y. S. Nasir and D. Guo, "Deep reinforcement learning for joint spectrum and power allocation in cellular networks," in Proc. IEEE Global Communications Conference Workshops (GLOBECOM Workshops), 2021, pp. 1–6.
16. I. A. Bartsiokas, T. A. Tsiftsis, and N. I. Miridakis, "ML-based radio resource management in 5G and beyond networks: A survey," IEEE Access, vol. 10, pp. 83507–83528, 2022.
17. Y. Azimi, S. Yousefi, H. Kalbkhani, and T. Kunz, "Applications of machine learning in resource management for RAN-slicing in 5G and beyond networks: A survey," IEEE Access, vol. 10, pp. 106581–106612, 2022.
18. A. Patil, S. Iyer, O. L. A. López, R. J. Pandya, K. Pai, A. Kalla, and R. Kallimani, "A comprehensive survey on spectrum sharing techniques for 5G/B5G intelligent wireless networks: Opportunities, challenges and future research directions," arXiv preprint arXiv:2211.08956, 2022.
19. L. Wang, J. Wu, Y. Gao, and J. Zhang, "Deep reinforcement learning based resource allocation for cloud native wireless network," arXiv preprint arXiv:2305.06249, 2023.
20. B. Sabir, S. Yang, D. Nguyen, N. Wu, A. Abuadbba, H. Suzuki, S. Lai, W. Ni, D. Ming, and S. Nepal, "Systematic literature review of AI-enabled spectrum management in 6G and future networks," arXiv preprint arXiv:2407.10981, 2024.
21. H. Zhang, N. Yang, W. Huangfu, K. Long, and V. C. M. Leung, "AI-empowered multiple access for 6G: A survey of spectrum sensing, protocol designs, and optimizations," Proceedings of the IEEE, vol. 112, no. 9, pp. 1264–1302, Sep. 2024.
22. S. Almani, "5G-resource-allocation-dataset: train_dataset.csv," GitHub, 2024. [Online]. Available: https://github.com/sulaimanalmani/5G-resource-allocation-dataset/blob/main/train_dataset.csv. [Accessed: Jun. 26, 2026].