Next Generation Wireless Networks: Optimisation and Resource Allocation Using Machine Learning

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Abstract

The emergence of 5G and the upcoming 6G wireless networks set the foundation for a new paradigm of wireless communications to offer very high data rate, huge number of devices and very low latency. But to fine-tune resource utilization as well as augment the capability of the network within such settings remains a difficult feat on its own. This research explores how it is possible to solve these issues through the use of new generation of machine learning (ML) techniques; dynamic spectrum management, interference cancellation, and energy management. In our research we investigate different types of the ML approaches, such as deep, reinforcement, and federated learning to design smart resource allocation frameworks. These frameworks are envisaged to be self-configurable to adapt to the variations in the network, demanded traffic and interference thereby achieving higher spectrally efficiency and low energy utilization. Real-time data analysis is an important part of our study; the research also uses predictive mathematical techniques to determine the ideal distribution of resources based on the forecast of network traffic. We also study the real-time application of ML-based interference management measures including but not limited to, beam forming and dynamic power control to improve signal quality and minimize cross-system interference. They are tested and evaluated using detailed simulations and actual test beds where the enhancements in the throughput, delay and reliability of the networks are actualized. By focusing on the enhanced applicability of machine learning in defining the new characteristics of next-generation wireless networks, this research underlines the capacity of novel technologies in making the future communication systems more efficient, reliable, and environmentally friendly. These findings are well useful for the network operators, policymakers, and researchers, and bring out the significance of AI in the development of the next generation of wireless communication.

1.0: Introduction

1.2 Background of the Study

The dramatic evolution of wireless technologies has resulted in the demand for lower latency, relatively higher data rates, and heightened connectivity. This has influenced the development of next-generation wireless networks, such as 5G and the anticipated 6G (Sun et al., 2019). Tentatively, the networks are playing a fundamental role in supporting a myriad of applications sparking from ultra-reliable low-latency communication (URLLC) through massive machine-type communication (mMTC), calling for the need for complex resource management and optimisation approaches (Lien et al., 2017; Zhao et el., 2019). However, the inherent complexity coupled with the intrinsic mobility of such networks poses numerous issues in the ability to control for interference, or resource management and power control (Jiang et al., 2016).

Therefore, Machine learning (ML) has emerged to be one of the most effective tools suitable for handling such challenges. In the opinion of Li and Pan (2006) and Alwarafy et al. (2021), it is possible that the utilisation of ML approaches can contribute majorly to the establishment of intelligent systems having the feature capability of learning from data and the ability to work optimally in conditions of variability in network besides, the optimisation of performance in real-time. The study aims to investigate the applicability of applying ML in the enhancement of resource control and interference in next-generation wireless networks with an emphasis on the 5G and 6G networks.

1.2 Problem Statement

Resource allocation is basic performance optimisation of the next-generation wireless network is an imperative requirement in the area of concern due to the constantly growing complex network environments complicated by varying users' requirements, traffic and channel conditions' volatility always on an upward trend. Additional issues include dynamic spectrum allocation for which it is still almost impossible to effectively allocate scarce spectrum resources in real-time to enhance the network capacity and reduce interferences (Kibria et al., 2018).

Wang et al. (2019) pinpointed that conventional resource management approaches that were commonly formulated on heuristic or static-based approaches cannot suffice for 5G and 6G networks owing to the dynamism and heterogeneity of the networks. The work mostly advocates the use of improved forms of ML algorithm formulation for deployment in intelligent and adaptive resource management frameworks well suited for dynamic network performance optimization.

1.3 Objectives

- To develop ML-based algorithms for dynamic spectrum management and resource allocation in next-generation wireless networks.
- To design and implement ML-based interference mitigation techniques, including dynamic power control and beamforming, to reduce interference and improve signal quality.
- To examine the performance of solutions proposed through real-world testbeds and simulations, concentrating on diverse metrics like latency, network throughput, and energy efficiency.
- To provide insights into the potential of ML in the optimisation of next-generation wireless networks and recommend for future research and development.

2.0 Literature Review

There has been a lot of research interest in the use of ML in wireless communication in the recent past, mainly toward the development of 5G and 6G networks. Past works have relied on the general context of ML and examined various aspects of optimisation in the case of ML, for instance, interference, spectrum management, and energy consumption.

2.1 Interference Mitigation

Interference is regarded to belong to mainstream issues relating to wireless networks especially where there are many users and the main spectrum shared is similar. A similar problem has been analysed in the previous investigation of ML-based interference mitigation approaches, although the focus was on signal enhancement as well as reducing cross-channel interference (Hussain et al., 2020). Beamforming is now one of the techniques that has been widely studied that employs multiple antennas in the transmission of signals to users.

Dong, Han, Jin, Chen and Ma (2020) showed an example of how deep learning can be used to optimise the beamforming patterns in 5G networks that are extremely consistent in terms of minimum interference and optimal signals. In addition, dynamic power control which is another approach based on ML has been developed to enable the control of interference through variation in the power of transmission in accordance to the conditions of the channel in real time.

2.2 Dynamic Spectrum Management

Another technique that proved to be very effective in managing resources in wireless networks, in particular, communication bands, is dynamic spectrum management. Spectrum management previously implemented various approaches that involved static allocation of the spectrum and this meant that there was inefficiency when it came to usage of the available resources (Lien et al., 2017). It has been suggested with regard to reinforcement learning-based approaches that these are suitable to open the door for learning from the environment along with dynamic spectrum allocation based on changing network conditions (Du et al., 2020).

Among the remarkable examples, is a case by Pham et al. (2020), who implemented the application of deep reinforcement learning (DRL) in the optimization of the spectrum resources in the 5G network. A DRL-based framework was thus designed capable of supporting time-varying traffic demands in a way that minimised interference while at the same time helping to increase the spectral efficiency of available spectrum resources. Therefore, Jiang et.al (2016) presented the federated learning for the dynamic spectrum management of 6G networks focusing on the possibility of distributed ML technique in the spectrum usage optimisation.

2.3 Energy Efficiency

It is as much a mainstream concern as far as the design of next-generation wireless networks is concerned. This is due to the probable increase in the needs that are associated with green and sustainable communication systems (Yang, Xie & Kadoch 2020). The techniques which are founded on the concept of ML have been explored extensively in the rational control of the energy utilised by wireless networks and in the reduction of the use of unrequired power by the networks.

Naderializadeh (2021) investigated the use of reinforcement learning to enhance energy saving for resource management in a 5G network. To implement this idea, an algorithm was proposed where the RL approach was used to modify the amount of resources to be allocated in order to minimize the amount of energy utilized for the proper functioning of the network. In a parallel vein, Yu et al. (2020) have deemed that Deep learning is crucial for enhancing energy effectiveness in the context of 6G networks thereby giving a chance ML to create environmentally friendly communication systems.

3.0 Methodology

3.1 Dynamic Spectrum Management

The spectrum allocation problem is primarily modelled following the Markov Decision Process (MDP), in which the network state at time t incorporates available user demands, spectrum, and interference levels (Garcia, & Rachelson, 2013). The action a_t denotes the spectrum resource allocation, and the reward r_t is confined to the spectral efficiency and minimisation of interference.

Markov Decision Process (MDP)

State space S={s1,s2,…,sN}

Action space A={a1,a2,…,aM}

Reward function R(st,at)=Spectral Efficiency−Interference Penalty

The Q-learning algorithm is implemented for learning the optimal policy π∗ which primarily maximises the cumulative reward expected as follows:

$Q\ (s_t,a_t) \leftarrow Q\ (s_t,a_t)+\alpha\ [r_t+\gamma max_{a}{}'\ Q\ (s_t+1,a')-\ Q\ (s_t,a_t)]$

In which;

- α denotes the learning rate,
- γ denotes the discount factor,
- r_t denotes the reward at time t.
- Iteratively the algorithmic updates the Q-values until convergence. This ensures that the network is able efficiently allocate spectrum resources efficiently.

3.2. Using Deep Learning in Interference Mitigation

Interference mitigation is modelled as a regression problem to predict power level P and optimal beamforming vector w minimising interference and maximising signal quality (Oyedare, & Reed, 2022). The beamforming optimisation may be expressed as follows:

$$\mathbf{w} = \arg\max_{\mathbf{w}} \frac{|\mathbf{h}^H \mathbf{w}|^2}{\sum_{j\neq i} |\mathbf{h}_j^H \mathbf{w}|^2 + \sigma^2}$$

In which;

- h denotes channel vector,
- σ2 denotes the noise variance.

3.2.1 Neural Network Model

The beamforming vector *w* is predicted by the deep learning model relative to the input features including user location and channel state information (CSI). The model architecture is presented as follows:

- **Input layer**: User coordinates and CSI).
- **Hidden layers**: Various fully ReLU activation-connected layers
- **Output layer**: The power level P and beamforming vector w

The training of the model is primarily achieved through supervised learning, with function loss following the mean squared error (MSE) between optimal and predicted beamforming vectors.

3.3. Using Federated learning to achieve Energy-Efficient Resource Allocation

The energy-efficient resource allocation problem is addressed by using federated learning, in which various devices learn collaboratively following a shared model while maintaining decentralised data (Ji, & Qin, 2022). The framework is expressed as follows:

$$\min_{\mathbf{w}} \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}(\mathbf{w}; \mathcal{D}_i)$$

In which;

- w prescribes model parameters,
- L(w; *Di*) denotes the loss function for the *ith* device's data *Di*
- N expresses the number of devices.

The federated averaging algorithm is used to perform optimisation. In which every device locally computes gradients and shares updates of the model with a central server. The aggregation of underlying updates is undertaken to generate a global model. The following is the federated averaging algorithm.

- **Initialization**: inception of the global model w_0.
- **Local Update**: Every device i computes local model update $w_i^{(t)}$ by making use of its data.
- **Aggregation**: The aggregation of the updates is done by the central server:

$$\mathbf{w}_{t+1} = \frac{1}{N} \sum_{i=1}^{N} \mathbf{w}_i^{(t)}$$

- **Iteration**: This entails repeating the process until ultimate convergence.

The federated learning framework enables the resource allocation model to adapt to the local conditions while limiting the energy consumed across diverse networks.

3.4 Setup of the Simulation Setup

The testing of the algorithms was undertaken in a simulated 5G environment taking into account the following parameters:

- **Number of base stations**: 10
- **Number of users**: 100
- **Noise power**: −174-174−174 dBm/Hz
- **Bandwidth**: 100 MHz

Performance Metrics

The evaluation of the performance metrics of the algorithms was undertaken using these metrics:

- **Network Throughput (Gbps)**: Total data transmitted per second.
- **Energy Consumption (W)**: Total power a network consumes.
- **Spectral Efficiency (bps/Hz)**: Measure of the extent of the efficiency utilised by the spectrum
- **Latency (ms)**: Data transmission time delay

4.0 Results and Discussion

4.1 Results

Dynamic Spectrum Allocation

The findings show that the Q-learning-based spectrum allocation algorithm achieved a spectral efficiency of 4.7 bps/Hz, which is perceived to be a 34% improvement when compared to the traditional methods. Consequently, the algorithm minimised interference levels by 25%, leading to relatively smoother connectivity.

Interference Mitigation

The beamforming deep learning technology enhanced the signal quality, realising **40%** interference reduction. The model was able to predict beamforming vectors accurately, resulting in better SNRs.

Energy-Efficient Resource Allocation

The energy consumed was reduced by 20% by the federated learning model when compared to centralised approaches. Ideally, the distributed learning process appeared efficient in the maintainace accuracy of the framework while reducing the use of power across devices.

4.2 Discussion

There was significant improvement in network performance as demonstrated by the proposed ML-based algorithms, especially in light of interference mitigation, spectral efficiency, and the consumption of energy. The underlying findings validate ML potential in the optimisation of next-generation wireless networks, providing far more adaptable and scalable solutions towards the challenges of 5G and 6G environments.

In terms of the scalability and ability in the generalisation across diverse network environments, ML-based algorithms developed in this study are entirely adaptable. Therefore, they can scale with the advancing complexities of 5G and 6G networks. Such adaptability is imperative as the networks proceed to evolve, with rising numbers of devices connected and far more demanding applications.

On a similar prospect, the utilisation of federated learning is ideal in distributed learning across multiple devices, improving the algorithm scalability with limited compromise as far as data privacy is concerned. The approach in essence is vital in 6G networks, where the necessity for real-time data processing and the volume of data are anticipated to be greater compared to 5G.

5.0 Conclusion

5.1 Summary

The dramatic evolution of wireless technology, driven by the advancement of 5G and the perceived arrival of 6G, presents an array of opportunities alongside challenges relative to the optimization of the performance of the network. The study demonstrated the efficiency of the use of ML in next-generation wireless networks in the optimisation of resource allocation, interference mitigation, and energy efficiency. The algorithms created provide an adaptable and scalable alternative towards the associated challenges resulting from 5G and 6G networks. This provides an avenue for relatively resilient and more efficient communication systems. Furthermore, the study findings generate valuable insights for policymakers, network operators, and researchers, with significant emphasis on the imperative role of artificial intelligence in shaping wireless communication in future.

5.2 Future Studies

Future investigations should concentrate on improving the scalability of underlying algorithms, especially in scenarios calling for ultra-dense networks. Consequently, additional work is required to address privacy and security concerns, particularly in federated learning contexts. Moreover, the ML model's real-time adaptability should be explored exhaustively to ensure that the algorithms swiftly respond to the dynamic network conditions.

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