A Deep Learning Approach for Optimizing ٥G Network Performance in Digital Government Services

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Abstract

٥th Generation or ٥G mobile network is designed to provide faster speed with reduced latency. The network has enhanced capacity and supports multiple devices. Digitalization enables governments to offer citizens and businesses greater access to essential public services. Thus, ٥G can support electronic government (e-government) services. However, e-government requires high bandwidth and support for several devices on the network, which are limited to ٤G. Therefore, there is a need to optimize ٥G for better performance and effectively manage all devices on the network. In this light, this study applies deep learning techniques based on a Deep Q-Network (DQN) model-based algorithm to a ٥G network for spectrum and resource management. The experiment includes ten base stations (BS) and one hundred randomly distributed user equipment (UE) nodes. Our findings show that DQN has a higher spectrum efficiency and throughput than the heuristic approach. Nevertheless, the heuristic approach demonstrated greater energy efficiency. DNQ had lesser packet loss and interference rates. This approach also had low latency. Results show that our approach can efficiently manage ٥G for digital government services. Additionally, it can provide more intelligent and dynamic learning solutions for wireless network optimization. Furthermore, our findings show that adopting deep learning for network optimization reduces network operators' dependency on manual resource allocation and optimization tuning. We conclude that governments can monitor public safety and manage traffic using an optimized ٥G network with low latency and high data reliability.

Keywords: ٥G network, resource allocation, spectrum, deep learning, network performance.

١. Introduction

The evolution of telecommunication towards more pervasive services has resulted in greater demand for reliable networks with low latency and high-data-rate connectivity. The rapid increase in data traffic necessitates a ٥G generation revolution for effective resource allocation and spectrum management in digital government services (Manukonda, ٢٠٢٣; Velayutham, ٢٠٢١). ٥G is a mobile network standard that offers higher upload and download speeds (Rischke et al., ٢٠٢١). Also, the technology provides high speeds, low latency, and massive capacity. Nevertheless, ٥G is limited due to several factors (George & Sagayarajan, ٢٠٢٣; Hussain & Khan, ٢٠٢٠; Hasnat et al., ٢٠١٩). Its limited size makes the narrow band to be easily congested. Also, regulation limits the dynamic sharing of the spectrum. In addition, power mismanagement results in harmful inter-user interference. Finally, the quality of service can be degraded due to balancing inter-user interference and spectrum window.

Governments need to ensure citizens and businesses have access to essential public services. Citizens expect these services to be more responsive, transparent, and efficient (Lynn et al., ٢٠٢٢). Hence, several governments have adopted technology to enhance service delivery. Digital government services or e-government involve government agencies leveraging technology to make services reliable, transparent, and accessible to citizens (Janssen et al., ٢٠٢١). They aim to enhance engagement between citizens and the government. Digital government services include e-government, e-health services, smart cities, social services, and open data platforms (Kwilinski et al., ٢٠٢٤; Bhuvana & Vasantha, ٢٠٢٠; Anshari & Lim, ٢٠١٧). Importantly, citizens should be able to access and pay for government services online. ٥G can potentially deliver optimal outcomes for government services (Volk & Sterle, ٢٠٢١). They can be leveraged to drive autonomous vehicles and support connectivity for virtual reality (VR) and augmented reality (AR) driven solutions. The COVID-١٩ pandemic resulted in the increase in digital government services (Moser-Plautz & Schmidthuber, ٢٠٢٣;

Pandey & Pal, ٢٠٢٠). Consequently, the government must adopt ٥G technologies with capabilities for greater network performance, including faster speeds and lower latency.

Network performance depends on the bandwidth and throughput (Rischke et al., ٢٠٢١). Hence, the quality and quantity of the network is essential. Lata et al. (٢٠٢٠) noted that network optimization seeks to enhance performance and reliability. This process includes the application of performance indicators and strategies to restructure and eliminate constricting factors to maximize the efficiency of networks. According to Martin et al. (٢٠١٨), an effective resource allocator is crucial when traffic control is complicated, costly, and burdensome. Not only are these service-oriented ٥G networks, such as e-health and smart cities, technically innovative, but conventional optimization needs to be improved. For instance, they struggle to coordinate multiple transmission parameters due to their structural complexity (Alsulami et al., ٢٠٢٢; Gures et al., ٢٠٢٠). Also, such infrastructures still need effective control mechanisms for optimizing the quality of service (QoS) of ٥G networks due to the sheer size of the networks (Alsulami et al., ٢٠٢٢; Gures et al., ٢٠٢٠). Thus, an active requirement exists to upgrade the ٥G network and meet the existing network constraints. A contradiction can be seen here as there is increasing demand on the ٥G to determine further layers that efficiently use resources and spectrum.

Artificial intelligence (AI) stimulates how human beings conduct tasks and make decisions (Soori et al., ٢٠٢٣). AI is used in various fields, including education, engineering, employment, marketing, and health (Wan et al., ٢٠٢٤; Xu & Ouyang, ٢٠٢٢; Haleem et al., ٢٠٢٢; Reddy et al., ٢٠٢٠). Meanwhile, deep learning allows computational models to learn data representations at multiple levels of abstraction (Soori et al., ٢٠٢٣). DL can enhance ٥G's efficiency, speed, and effectiveness for greater flexibility and responsiveness in real-time tasks (Ahmed et al., ٢٠٢٢; Abubakar et al., ٢٠٢٠). Thus, this strategy can be employed to enhance ٥G network performance. Accordingly, this research uses DL methods to optimize ٥G network service to support e-government applications and service delivery wholly.

٢. Background

٢,١. ٥th Generation Network

The ٥G technology is a global wireless standard after the fourth-generation (٤G) aimed at improving the capabilities, characteristics, and speed of the existing mobile networks using three classes of services (Rischke et al., ٢٠٢١). It is achieved through flexible numerology, multiple access, and bandwidth part schemes in the physical layer (Sadi et al., ٢٠٢٠). ٥G offers lower latency than ٤G (Hajlaoui et al., ٢٠٢٠). The network also allows more devices to connect to it. Additionally, ٥G's wide bandwidth, low latency, and universal connectivity can support smart cities, intelligent transport, edge computing, e-health, virtual reality, and robotics (Shafique et al., ٢٠٢٠; Ahad et al., ٢٠٢٠). Nevertheless, ٥G needs to be dynamic to effectively manage the increasing demand of users and devices (Gures et al., ٢٠٢٠). Hence, there is a need to optimize the performance of the ٥G mobile network for more efficient and reliable services.

٢,٢. Resource Allocation in ٥G Networks

Fundamentally, the resource allocation algorithm directly affects the performance and efficiency of the ٥G network (Su et al., ٢٠١٩). However, the ٥G multidimensional service model includes different services with delay and throughput requirements (Halabian, ٢٠١٩). Therefore, the traditional classical resource allocation method needs help to meet these requirements. In ٥G, resource allocation is done using different approaches. Such methods include dynamic spectrum sharing, edge computing, network slicing, beamforming, and massive MIMO (Muntaha et al., ٢٠٢٣; Ahmad et al., ٢٠٢٠). Other methods include QoS-based user-centric management, energy-efficient technologies, CoMP-based interference management, load balancing, and policy-based automated adjustments (Simsek et al., ٢٠١٩; Hossain et al., ٢٠١٩). For example, load balancing is applied for optimal traffic distribution, while edge computing reduces latency and improves resource efficiency. However, multidimensional, time-based, and vast demand for resources and services limits ٥G resource allocation approaches based on adaptability, scalability, accuracy, and data model. To maximize ٥G's performance for e-government, the spectrum must be effectively managed. In a crowded radio frequency (RF) environment, interference can affect spectrum allocation. As a result, network operators usually operate with limited spectra at higher frequencies. Thus, effective optimization methods are warranted for these challenges. Optimizing ٥G network performance will be beneficial to e-government services.

٢,٣. Traditional Methods vs Deep Learning Approaches

Existing literature on ٥G resource allocation and management is mainly based on heuristic, mathematical models, and rule-based methods (Kamal et al., ٢٠٢١). AI, operations research, control theory, networking, and mathematical modeling are essential in developing mathematical models (Hassannataj Joloudari et al., ٢٠٢٤). The existing mathematical models are developed based on the existing cellular networks. Hence, each model is built to handle a cellular network differently. However, the mathematical model is limited by availability, power allocation, user association, channel capacity, bandwidth distribution, cell load, and interference management (Kamal et al., ٢٠٢١; Santos et al., ٢٠٢٠). Furthermore, they cannot handle changing traffic volume, quality of service, mobility, error rates, and channel quality (Hassannataj Joloudari et al., ٢٠٢٤). In sum, the traditional methods use linear optimization for resource and time slot allocation, limiting their performance concerning accuracy and efficiency. This is because it requires heavy computation.

AI and learning-based techniques can be applied in next-generation mobile networks to process extensive data and predict the behavior of systems (Zappone et al., ٢٠١٩). The AI-based model can learn and classify historical data patterns in mobile networks. This approach is applied to operational networks' robustness. Studies show that deep learning-based approaches outperform conventional mathematical models (Ahmad et al., ٢٠٢٣; Prakash et al., ٢٠٢٠; Dia et al., ٢٠٢٠). They utilize data-driven models to improve the function, delays, throughput, bandwidth allocation rates, and quality of service (Hassannataj Joloudari et al., ٢٠٢٤). Moreover, deep learning makes the network more adaptable to dynamic conditions and complex networks.

٢,٤. Deep Learning Models for Resource Allocation

Various models are employed in the ٥G network to address resource allocation. These models are usually classified into supervised, unsupervised, and reinforcement learning-based techniques (Yaliniz & Ikizler-Cinbis, ٢٠٢١). They utilize historical information containing network parameters to train the models and predict future scenarios. Meanwhile, unsupervised models do not require historical information. Notably, the models are more adaptable to different environments for resource allocation issues. Several hybrid models have been proposed to address the limitations of these models (Sevgican et al., ٢٠٢٠). For example, they are applied to resolve resource allocation issues. Deep learning has effectively optimized learning tasks (Zaheer & Shaziya, ٢٠١٩). Studies have applied neural networks for resource allocation (Qidan et al., ٢٠٢٢; Narottama & Shin, ٢٠٢١; Lee, ٢٠١٨). Nonetheless, a few studies have explored resource allocation in ٥G networks (Oulahyane et al., ٢٠٢٤; Xu et al., ٢٠٢١; Kamal et al., ٢٠٢١).

٣. Method

This study explores a deep-learning approach to resource allocation and spectrum management. The experiment was conducted using a custom-built network simulator in a simulated ٥G network environment. We included ten (١٠) base stations (BS) and one thousand (١٠٠٠) user equipment (UE) nodes distributed across the coverage area randomly. The BS average frequency is ٢٠ MHz, and the area covers a radius of ٥٠٠ meters per BS for moderate interference. A transmission power of ٢٠ dBm is recommended (Kim et al., ٢٠١٨). Furthermore, we implemented resource allocation and spectrum management. The proposed maximum user speed is ١٠m/s to reduce mobility, and the Rayleigh fading channel mode is used.

A deep Q-Network (DQN) model-based algorithm was adopted to maximize the UE's throughput while enhancing coverage and decreasing drop rates. Meanwhile, we employed the heuristic algorithm as a baseline to allocate resources across the UEs using its signal-to-noise ratio (SNR). Table ١ shows the DQN model's configuration

Table ١ Deep Q-Network-based Configuration

Input	**signal-to-noise ratio (SNR), user demand, and UE interference levels**
Hidden layers	**Two fully connected layers with ١٢٨ and ٦٤ neurons using ReLU activation**
Output	**Bandwidth and power levels for each UE**
Learning rate	**٠,٠٠١**
Discount factor (γ)	**٠,٩٩**
Exploration rate (ε)	**٠,١ decayed over time**

٣,١. Formulation

Signal-to-Noise Ratio (SNR) is calculated using:

$$\boldsymbol{SNR} = \frac{P_t - L}{N_\cdot + L}$$

Pt (dBm) is the transmission power, L is the path loss, and the noise power is $N_\cdot$(dBm): $N_\cdot = ١٠ log_{١٠}(k \cdot T) + ٣٠$ k indicates Boltzmann's constant and T is the temperature (Kelvin). The throughput T, is calculated using Shannon's capacity formula:

$$T = B\ log_{٢}(١ + SNR)$$

The bandwidth is represented with B. Heuristic Algorithm ($SNR_{i.}$) allocated to UE_i. Furthermore, our DQN Model includes action space which is the possible resource allocation and state space which is the current state of the network (Guo et al., ٢٠٢١; He et al., ٢٠١٥). Additionally, the model utilizes the reward function which increases the throughput while reducing drop rates.

٤. Results

The critical performance metrics of the ٥G network using DQN versus heuristic methods are shown in Table ٢. The simulation included ١,٠٠٠ steps for latency, spectrum efficiency, network throughput, and interference. The DQN-based strategy exhibited a considerable spectrum efficiency level of ٦,٢٨ bps/Hz, higher than that of the heuristic method (٤,٢٦ bps/Hz). As for latency, the DQN approach took less time (١٥,٨ ms compared to ٢٨,٤ ms in the traditional method), aligning with previous studies (Zhang et al., ٢٠٢٢; Jie et al., ٢٠٢١). Thus, the DQN method improved healthcare, finance, and logistics response times. Furthermore, use cases in autonomous vehicles (AV) or augmented reality (AR) can take advantage of the lowered latency for faster decision-making and enhanced user experience.

Table ٢ Performance Metrics

Metric	DQN-Based Approach	Traditional Heuristic Approach
Average Network Throughput (Mbps)	١٢٥,٦	٨٥,٢
Spectrum Efficiency (bps/Hz)	٦,٢٨	٤,٢٦
Latency (ms)	١٥,٨	٢٨,٤
Interference Reduction (%)	**٢٥٪ reduction**	**Baseline (No reduction)**
Resource Allocation Fairness	**High (adaptive to traffic)**	**Moderate (fixed allocation)**
Energy Consumption (Joules)	٥٠,٣	٣٨,٩
Convergence Time (steps)	**٥٠٠ steps**	**-**
Packet Loss Rate (%)	٢,٥	٥,٨
QoS Satisfaction Rate (%)	٩٦,٢	٨٥,٥
Computational Overhead	**Moderate**	**Low**

	(requires GPUs/edge processing)	(minimal processing)

٤,١. Network Throughput

Table ٣ demonstrates the average resulting network through DQN-based approaches and heuristic methods (in bps). We showed that the average DQN with a proposed procedure algorithm achieved a ٤٧,٤٪ success rate. Our findings align with the study of Alablani and Alenazi (٢٠٢٣). A significant benefit of our approach is that it can increase throughput, making networks more efficient and reliable (Moazzeni et al., ٢٠١٨; Umar et al., ٢٠١٤). Therefore, DQN can support larger inputs. This is essential for real-time processing systems with limited resources that have heavy data-intensive users and rapidly changing conditions.

Table ٣ Average Network Throughput

Algorithm	Average Throughput (Mbps)
DQN	١٢٥,٦
Heuristic	٨٥,٢

٤,٢. Spectrum Efficiency

Table ٤ shows that a higher spectrum efficiency was observed in the DQN model than heuristic. This outcome was because our model allocateed resources dynamically based on real-time channel conditions. We observed that increased spectrum efficiency could result in faster user data rates (Periyathambi & Ravi, ٢٠٢٤). It also allows the spectrum to support more devices, especially during peak periods.

Table ٤ Spectrum Efficiency

Algorithm	Spectrum Efficiency (bps/Hz)
DQN	٦,٢٨
Heuristic	٤,٢٦

The DQN model showed a ٢٥٪ reduction in interference levels compared to the heuristic method by making intelligent resource allocation decisions, especially in overlapping coverage areas. The training loss and reward throughout the simulation indicate that the DQN model converged after approximately ٥٠٠-time steps. Subsequently, the network performance stabilized, showing ideal resource allocation results. Our findings show DQN-based system is more beneficial than the heuristic algorithm, especially in managing network throughput and spectrum efficiency (Lee et al., ٢٠٢٠). We observed that DQN reduced network interferences due to effective bandwidth and power allocation to each user equipment.

Moreover, the results affirm that the DQN model can effectively optimise ٥G network performance. The simulation showed fewer interferences, confirming that deep learning techniques can adequately handle ٥G spectrum resources (Pavani et al., ٢٠٢٣; Almutairi et al., ٢٠٢٢). Our experiment established that deep learning could perform highly accurate dynamic spectrum sensing to identify accessible spectrums (Ahmed et al., ٢٠٢٢). It can learn complex patterns and adapt accordingly. Furthermore, low latency can improve ٥G-based applications like virtual laboratories, industrial automation, IoT, autonomous vehicles, smart cities, and e-health (Perfecto et al., ٢٠٢١; Ran et al., ٢٠١٨). This enhanced communication will ensure that the government provides citizens faster and more reliable services. In turn, citizens will be more responsive to government services. The DQN-based procedure showed relatively less interference, positively affecting downstream throughput and minimizing packet loss (Razavi et al., ٢٠٢١). This is a critical need in urban areas with high customer density where spectrum sharing is necessary. Consequently, this approach can save costs by eliminating the need for additional base stations to mitigate interference.

٥. Conclusion

This study demonstrates the feasibility of using deep learning methods to optimize resource allocation and spectrum management in ٥G networks. So how do we take service delivery to the next level? Optimizing digital government services. This study proposes ways to find the best methods for optimizing network performance, and it wants those relevant findings to demonstrate that neural network architectures can effectively reduce resources and spectrum. Our results show that using DQN leads to better spectrum efficiency and throughput than using classical heuristic baselines, while achieving lower packet loss rates. Based on the results, DQN also exhibited lower latency and interference, further validating DQN as a potential game-changing solution for next-generation wireless communications.

Nonetheless, it is important to stress the fact that the heuristic approach reduced energy consumption when compared to DQN. Deep learning and artificial intelligence algorithms can provide intelligent adaptive methods for navigating the complexities associated with today wireless networks, and this has been reflected in the numbers. In future, adoption of these technologies can improve citizen experience and streamline operations for critical services (Tyagi & Chahal, ٢٠٢٠). Finally, these outcomes enrich the quickly developing area in powerful deep learning for mobile network optimization of effective digital government services. In particular, it has the potential to improve resource allocation and radio spectrum management in mobile networks. Thus, it eliminates the need for network operators to depend on manual tuning for resource allocation and optimization. Deep learning can learn to enhance spectrum efficiency and minimize operational costs by managing spectrum resources dynamically. Consequently, it will provide more responsive, transparent, and accessible services to citizens. This is useful when governments implement ٥G networks with scarce spectrum and expensive resources. Furthermore, operators can efficiently manage the spectrum and reduce operational overhead to improve their return on investment (ROI) and reduce bit for data transmission cost.

Since the study was limited to primary real-world conditions, landscape, physical structures, weather conditions, and specific devices can affect the outcome (Igbekele & Zhimwang, ٢٠٢٤; Faleti et al., ٢٠٢١; Siegel et al., ٢٠١٧). Hence, such aspects could influence the generalizability of the results in a real-world environment or government institutions. Also, the experiment is limited to ١٠ base stations and ١٠٠ user equipment nodes. However, this is a significantly smaller scale than government ministries or agencies. More extensive networks in government buildings may be prone to more interference than the scale of real-world ٥G deployments. Future studies could apply real-world situations and consider real-time performance, scalability, interference, weather, quality of service, or multiple devices.

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