

SMART POWER ALLOCATION IN MOBILE SYSTEMS USING DEEP LEARNING: AN EMERGING FIELD SURVEY

Dr. Nilesh Jain¹

¹ Associate Professor, Department of Computer Science and Applications, Mandsaur University, Mandsaur, India,
nileshjainmca@gmail.com

Abstract: The rapid expansion of mobile connectivity, driven by the widespread use of smartphones, IoT devices, and advanced applications like UAVs, driverless cars, and smart cities, has put wireless networks under previously unheard-of pressure. It is anticipated that fifth-generation (5G) and soon-to-be sixth-generation (6G) systems would provide exceptionally high data speeds, very low latency, extensive device connections, and enhanced energy efficiency. Meeting these requirements calls for intelligent and adaptive resource management, with power allocation playing a central role in ensuring spectral efficiency, energy sustainability, and quality of service (QoS). Conventional techniques, including water-filling, game theory, and convex optimization, have been widely used but face limitations when applied to dynamic, heterogeneous, and large-scale environments. Recent years have seen the rise of deep learning (DL) as a potent technique that can handle the high-dimensional, time-varying, and nonlinear characteristics of mobile communication systems. DL-based techniques allow for distributed, data-driven, real-time power allocation through the use of models including deep neural networks, convolutional and recurrent architectures, reinforcement learning, and federated learning. These approaches demonstrate strong adaptability across diverse scenarios, including 5G/6G networks, IoT ecosystems, vehicular communications, and UAV systems. Together, they represent a transformative step toward achieving more efficient, scalable, and intelligent wireless communication.

Keywords: Smart Power Allocation, Deep Learning, Mobile Systems, Wireless Networks, Energy Efficiency.

1 INTRODUCTION

The incredible advancements in data transfer have drastically changed wireless networks. As expected, the quantity of wireless gadgets has been increasing at an astounding rate[1]. Soon, there noticeable increases in connection and traffic volume, a far wider variety of usage scenarios, and a society that is more mobile and connected. The volume of traffic has considerably grown. Between 2010 and 2030, data traffic is predicted to increase more than 20,000 times globally. Wearables and smart gadgets are expected to become more commonplace, even if smartphones are still expected to be the most popular personal electronics. To meet the constantly changing needs that previous system generations could not, the fifth-generation (5G) cellular communications technology must be widely deployed.

Providing mobile services that require high speed, ultra-low latency, high dependability, and energy economy remains challenging, despite improvements in 4G wireless network technology. These requirements have therefore become critical design goals for fifth-generation (5G) and beyond (B5G/6G) mobile networks. In order to maintain high user quality of experience (QoE), instant cloud services, interactive Internet, improved vehicle-to-everything (eV2X), large-scale IoT, and drone or robotics-based connection, current 4G/LTE infrastructures are insufficient[2]. Consequently, the past decade has witnessed substantial advancements in transmission and mobile hardware capabilities, ranging from compact smartphones to processors and memory capacities that rival modern laptops [3].

This technological transformation is reshaping the way live, work, and communicate [4]. Emerging applications such as autonomous vehicles, artificial intelligence (AI)-enabled services [5], The need for dependable, energy-efficient, and adaptable wireless communication is rising as smart factories, smart homes, and drone-based delivery systems proliferate. The integration of human-machine interaction in future wireless environments further amplifies the need for cost-effective and intelligent resource management strategies.

The anticipated growth in mobile connectivity is expected to generate massive traffic volumes, heterogeneous services, and multidimensional performance requirements [6]. In order to meet this demand, spectral efficiency in future mobile networks must grow by about a thousand times when compared to previous generations. For instance, while fourth-generation (4G) systems achieved spectral efficiency improvements of approximately 5–15 times, the leap toward 5G and beyond requires far more advanced solutions.

To address these demands, 5G networks use supporting technologies such device-to-device (D2D) connectivity, software-defined networking (SDN), and the IoT[7][8]. The Internet of Everything (IoE) is made possible by a number of technologies, including network slicing, cloud radio access networks (C-RAN), mobile edge computing (MEC), unmanned aerial vehicles (UAV), vehicle networking, and machine-to-machine (M2M) communication. However, such a highly heterogeneous and resource-intensive ecosystem poses major challenges in power allocation, where energy must be intelligently distributed across users, devices, and base stations to ensure both energy efficiency and service quality.

In this context, a revolutionary method for intelligent power distribution in mobile systems is deep learning (DL). Unlike traditional optimization and heuristic-based techniques, DL offers data-driven adaptability, scalability, and real-time decision-making, making it highly suited for the dynamic and complex requirements of 5G and beyond[9]. This survey paper, therefore, examines the most recent developments in DL-based power allocation methods, analyzes their advantages and limitations, and identifies open challenges and research opportunities in building energy-efficient, intelligent, and sustainable mobile communication systems.

1.1 Structure of the Paper

The paper is organized as follows: Section 2 covers the fundamentals of power allocation in mobile systems, while Section 3 discusses deep learning in wireless communication. Section 4 highlights key challenges in applying deep learning for mobile power allocation, and Section 5 presents applications in 5G/6G and related networks. Section 6 reviews recent literature, and Section 7 concludes with insights and future research directions.

2 FUNDAMENTALS OF POWER ALLOCATION IN MOBILE SYSTEMS

In mobile communications, power allocation is the process of assigning the transmission power to the users of wireless networks, wireless devices and the base stations. The main objective is to provide a reliable communication at maximum spectral efficiency with minimum interference and minimize the energy consumption[10]. In the multi-user and multi-cell environment, optimal power allocation has a direct influence on the overall system performance in terms of achieving a balance between quality of service (QoS) of individual users and network fairness as well as network stability.

The role of power allocation is complex; it not only ensures that each user is given enough transmission power to sustain connectivity, but it also limits the interference of others who share the same spectrum. On the system level it helps save energy costs of running the base stations, and reduces the rate of discharging the mobile device batteries. Moreover, the different needs of new services in 5G and beyond, that is, enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable low-latency communications (URLLC), require power allocation. Power allocation is an adaptive way to dynamically adjust the transmission power of nodes in the network based on the network topology, traffic demand, and channel conditions which allows modern mobile systems to be truly scalable, efficient and sustainable.

2.1 Key Objectives of Power Allocation

For mobile communication systems to function effectively and meet the needs of various applications, power allocation is essential. The primary objectives include:

- **Energy Efficiency (EE):** Efficient power allocation minimizes total energy consumption in mobile devices and base stations and increases battery life of mobile devices and also reduces the cost of operations. In the IoT and ultra-dense networking cases, where it is necessary to deploy large numbers of devices, sustainability of communication requires energy-efficient communication systems.
- **Quality of Service (QoS):** The power distribution has a direct effect on the potential to fulfill service-level requirements including the data rate, latency, and reliability. Adequate power levels to support various users and applications ensure a consistent QoS, in heterogeneous environments.
- **Spectral Efficiency (SE):** The optimal distribution of power among resources in available frequency bands allows networks to achieve maximum spectra utilization to carry Higher data rates and support more users within a limited bandwidth.
- **Interference Management:** Interference is a major performance limitation in the case of multiple cells and users. By allocating power, co-channel and inter-cell interference are mitigated, making communication more stable and resource utilization more efficient.

2.2 Traditional Techniques for Power Allocation

There are various conventional methods that have been used to maximize power distribution in mobile systems. The previously successful techniques are not without an issue of scalability and flexibility as we introduce 5G and beyond. Common methods: Typical methods involve the use of software that is capable of handling the EDW system under consideration and manipulating the data:

- **Water-Filling Algorithm:** A traditional optimization-based approach that distributes more power to channels with good conditions (high signal-to-noise ratio) but minimizes that to poor channels[11]. This method maximizes overall capacity but assumes accurate channel state information.
- **Game Theory Approaches:** Treats power allocation as a strategic game among multiple users or cells, where each participant aims to maximize its utility (e.g., data rate) while minimizing interference to others. Equilibrium-based solutions, such as Nash Equilibrium, are widely applied in distributed resource allocation.
- **Convex Optimization Methods:** Formulate power allocation as a convex optimization problem, allowing efficient computation of globally optimal solutions under specific constraints (e.g., minimizing total power while ensuring QoS). These approaches provide strong theoretical guarantees but may be computationally intensive in large networks.
- **Heuristic and Rule-Based Methods:** Simplified approaches that rely on fixed rules or iterative algorithms to allocate power based on predefined conditions. While computationally efficient, these methods often sacrifice optimality and adaptability in dynamic environments.

2.3 Power Allocation in Mobile Communication Systems

These days, wireless communications have changed people's life by making it possible to communicate information reliably, continuously, and remotely from any location. Significant improvements in signal processing techniques, physical infrastructure, and the availability of strong, affordable technology have all contributed to this change. Mobile phone multimedia services, Wi-Fi Internet access, and WiMAX-enabled smart-grid applications are a few examples of this technological revolution.

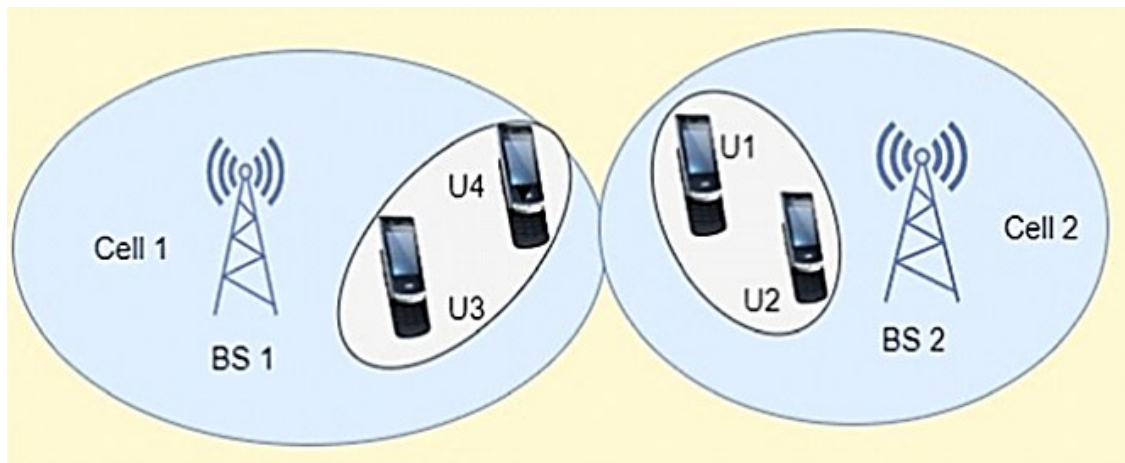


Figure 1: Mobile Communication Systems

Improved signal processing and affordable hardware Cellphones, Wi-Fi, smart-grids, and WiMax are examples of this technological revolution. As more devices prefer wireless connection, Figure 1 shows the need to handle the rising interference from wireless devices in radio communication channels[12]. Wireless information transfer must meet QoS criteria for data, voice, or video communications over the required communications service. For this, communications and signal processing communities have offered numerous techniques.

2.4 Traditional Approaches Vs. Smart Approaches

Manual procedures like phone assistance, email advertising, and in-person contacts are common in traditional customer engagement. While they might be useful in some situations, these methods frequently find it difficult to expand and adjust to the quickly shifting demands of their clients. Traditional methods were found to excel in scenarios requiring high levels of empathy, trust-building, and nuanced understanding[13]. For example, in the healthcare and financial sectors, where sensitive and complex issues often arise, customers preferred direct interaction with human representatives.

Smart Approaches

Smart technologies affect healthcare, transportation, energy, and mobility. AI, IoT, sensors, and data analysis can boost efficiency, production, and safety. Ambient Assisted Living, Smart Home Technology, Welfare Technology, and mHealth are all utilized in smart health research[14]. These terms refer to the vast array of technical services and artefacts that improve prevention, identification, diagnosis, treatment, and oversight of health problems in the workplace and in daily life. Intelligent mobility has been extensively studied in smart city research. Identify seven research clusters in their thorough smart mobility technology review. Safe and efficient urban computing, Energy- and pollution-saving solutions, Advanced sensors and digital technology for mobility management, sharing, Smart energy systems enhance energy consumption monitoring, renewable energy integration, grid management, and energy efficiency.

As shown in Table 1, the comparison highlights a shift from traditional manual and standardized methods to AI-driven, data-centric smart approaches, enhancing scalability, personalization, and efficiency while introducing challenges related to privacy, security, and technological dependency.

Table 1: Traditional Approaches vs. Smart Approaches

Aspect	Traditional Approaches	Smart Approaches
Customer Engagement	Manual techniques including in-person contacts, email marketing, and phone support.	AI-driven chatbots, personalized digital platforms, real-time data-driven engagement.
Strengths	High empathy, trust-building, nuanced understanding; suitable for sensitive issues (e.g., healthcare, finance).	High scalability, adaptability, automation, efficiency, and personalization across domains.
Assessment & Evaluation	Relies on formative, summative, and standardized testing; provides reliability and objectivity through standardized methods.	Data-driven monitoring, adaptive testing, continuous feedback through smart systems and AI analytics.
Domains of Application	Education, healthcare, finance, customer support.	Healthcare (mHealth, AAL, smart homes), transportation (smart mobility), energy (smart grids, renewable integration), urban management (smart cities).
Limitations	Struggles with scalability, adaptability, and real-time responsiveness.	Concerns about data privacy, security, cost, and over-reliance on technology.
Examples	Direct consultation with doctors, standardized school testing, manual energy monitoring.	AI-powered diagnosis, IoT-enabled patient monitoring, smart traffic management, smart energy grids.

3 DEEP LEARNING IN WIRELESS COMMUNICATION

Modern wireless communication systems have seen a revolution thanks to deep learning (DL), a technique that can identify intricate, non-linear patterns in high-dimensional data. Unlike conventional model-based approaches, DL enables data-driven decision-making, making it highly suitable for dynamic and heterogeneous mobile environments such as 5G and beyond[15][16]. Several deep learning architectures and frameworks are particularly relevant to communication and power allocation.

- **Deep Neural Networks (DNNs):** DNNs are multilayer feedforward neural networks capable of approximating complex functions. In communication systems, DNNs are applied to channel estimation, interference management, and power allocation by mapping input features (e.g., channel conditions, user demands) to optimized resource allocation decisions.
- **Convolutional Neural Networks (CNNs):** CNNs, which were first created for image processing, are excellent at spotting spatial patterns. In wireless communication, CNNs are used to process structured data such as channel state information (CSI) matrices discussed in figure 2, enabling efficient spectrum sensing, modulation classification, and adaptive power distribution across multiple subcarriers.

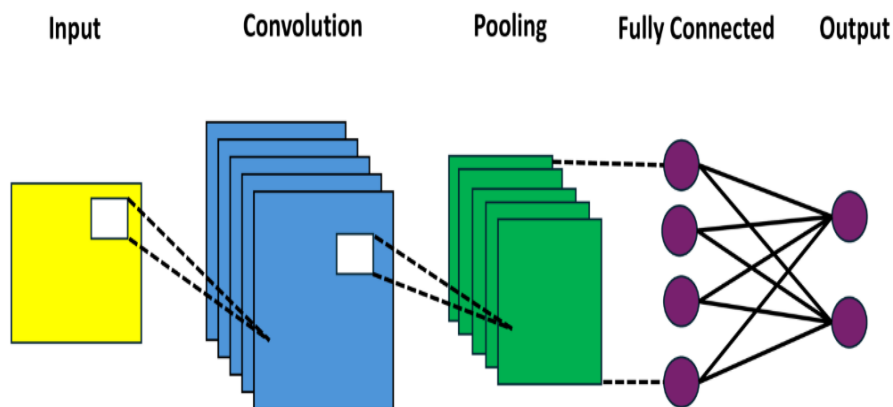


Figure 2: Architecture of a Convolutional Neural Network

- **Recurrent Neural Networks (RNNs):** RNNs are made to capture temporal relationships in order to represent sequential data[17]. This makes them particularly useful in time-varying wireless environments, where user mobility, traffic load, and channel conditions change dynamically. By using variations such as Long Short-Term Memory (LSTM) networks, power regulation has been optimized in accordance with traffic pattern prediction.
- **Reinforcement Learning (RL):** An agent learns optimum policies in RL's interactive learning paradigm through interactions with incentives and the environment. In mobile networks, RL is used for dynamic power control, resource

allocation, and interference coordination, especially under conditions where the network state is partially observable or highly dynamic.

- **Federated Learning (FL):** A number of devices collaborate to train a shared model without exchanging raw data using FL distributed learning methodology. The method has a significant applicability to mobile systems by supporting privacy preserving and scalable power assignment with minimal communication overhead based on local information at users and base stations.

3.1 Why Deep Learning Suits Mobile Systems

Mobile communication systems are complex, dynamic and high-dimensional in nature with varying degrees of users, dynamic wireless channels and varied service requirements. Conventional model-based optimization techniques have had difficulty addressing these issues, in large part because they require simplified assumptions and computationally demanding optimization algorithms[18]. Compared to this, Deep Learning (DL) offers a number of benefits that makes it specifically suited to mobile systems:

- **Modeling Nonlinear Relationships:** The wireless environment is distinguished by frequency-dependent nonlinearities due to fading, interference and user mobility. Many of the known DL methods particularly deep neural networks have been proven useful when it comes to approximating complex nonlinear functions and therefore, they can be used to capture the complicated nature of the relationships that exist between channel state information (CSI), user demands and power allocations decisions.
- **Scalability to Large Networks:** The rapid development of 5G, and soon-to-be-built 6G networks has equaled the number of devices, antennae, and communication lines being introduced into the market in exponential amounts. Real-time decision-making across diverse infrastructures is made possible by DL models' ability to be generalized to support massive-scale networks after being trained on enormous datasets.
- **Handling High-Dimensional Data:** Mobile systems generate vast amounts of data, including CSI matrices, mobility patterns, and traffic statistics[19]. Traditional methods often suffer from the "curse of dimensionality," whereas DL architectures like CNNs and RNNs can efficiently extract low-dimensional representations and learn hidden structures, making resource allocation more effective.
- **Adaptability to Dynamic Environments:** Communication systems are constantly changing due to variations in user mobility, spectrum availability, and network traffic. DL models, particularly those integrated with reinforcement learning, can adapt to time-varying conditions and continuously improve power allocation strategies through online learning.

3.2 Emerging Trends and Future Directions

The application of DL to smart power allocation in mobile systems is still in its infancy, making it a rapidly emerging field of research[20]. While traditional optimization-based methods have been studied extensively, their scalability and adaptability to 5G-and-beyond networks remain limited. Deep learning offers new opportunities, but several emerging directions highlight why this area is still evolving:

- **Acceleration and Optimization of DL Models:** The rise of IoT and ultra-dense 5G/6G deployments, there is a need for lightweight, Real-time power allocation using low-power deep learning models that can function effectively on edge devices. Research on model compression, quantization, and neural architecture search is critical to enable practical adoption.
- **Distributed and Federated Learning in Power Allocation:** Federated learning is a novel approach to learning that safeguards privacy, allowing multiple base stations and devices to collaboratively optimize power consumption without sharing raw data. This is particularly important in heterogeneous and sensitive environments like healthcare IoT or vehicular networks.
- **Integration with Edge Intelligence and Mobile Edge Computing (MEC):** Edge computing complements deep learning by bringing computation closer to users. Deploying intelligent power allocation strategies at the edge can reduce latency and enable adaptive decision-making in real time.
- **Security and Trustworthy Deep Learning:** As DL-based power allocation becomes widespread, ensuring robustness against adversarial attacks, spoofing, or data poisoning becomes crucial[20]. AI models that are secure and comprehensible are crucial for mission-critical applications like UAV networks and autonomous driving.
- **Towards 6G and Beyond:** The transition to 6G involves extreme heterogeneity, integration of AI-native architectures, and support for Internet of Everything (IoE). Smart power allocation in this era rely heavily on DL-enabled autonomous decision-making, creating a new research frontier.

4 CHALLENGES IN APPLYING DEEP LEARNING FOR MOBILE POWER ALLOCATION

Challenges in applying deep learning for mobile power allocation mainly arise from the high computational complexity of deep models, which limits deployment on resource-constrained mobile devices. Data availability and quality also pose issues, as real-world mobile network datasets are scarce and often heterogeneous. Ensuring generalization across diverse and dynamic network

scenarios remains difficult, leading to performance gaps. Additionally, privacy and security concerns in distributed or federated learning frameworks further complicate large-scale adoption.

4.1 Computational Complexity in Mobile Devices

Mobile users have the option of widespread deployment or local computing. The offloading procedure is shown by the up arrow. First, the edge server receives computations from mobile devices. By enhancing matrix multiplication, reducing numeral precision, and other means, computation acceleration often accelerates forward propagation. A tensor-based multiplication between a dense matrix and a sparse matrix is suggested in Park's work for quick calculation. When multiplying matrices, it pre-locates the values that are zero to save computation[21]. Because they simplify daily tasks, smart phones have become an essential element of life. Smartphones may be used anywhere and at any time thanks to capabilities like Wi-Fi, online surfing, and GPS navigation. Notwithstanding all of these cutting-edge capabilities, the main problems have with these smartphones are their short battery life, little data storage capacity, restricted bandwidth, etc.

4.2 Data Availability and Real-Time Adaptation

This technology came into prominence during Big Data and Real-Time Analytics and also forms an essential component of Modern Computer Architecture. By using CDC, real-time changes in the source tables may be recorded and analysed, which makes it possible to integrate the changes into target systems or provide clients with fast updates so they can learn from local data. Federated learning also makes it possible to adapt in real-time and enhances model performance. Data Gathering and Exchange: Businesses usually merge data from several sources, which might reveal private user information because AI systems require a large amount of data to learn well[22]. Data-sharing agreements and cooperative data analysis programs can exacerbate these problems, especially when data is exchanged across international borders with disparate privacy rules. Adaptive Modeling for real Time data analysis with machine mastering entails the choice of a suitable gadget learning model. That is primarily based on assessing the data and necessities of the mission and identifying the characteristics that want to be taken into consideration for the layout of the version.

4.3 Generalization Across Different Mobile Network Scenarios

In order for any educational field to function properly and be able to offer its services to authorised users, systems must be protected, whether on the client or server side. This difficulty relates to protecting to avoid and defeating attacks, the systems and putting in place suitable security rules and procedures[23]. Furthermore, it calls for safeguarding the integrity, confidentiality, and privacy of the data sent and preserved for the educational process. The work in question focuses on MCL, or mobile collaborative learning. Although a number of supporting architectures and frameworks have been established to improve MCL, the authors note that no literature has yet been written about improving the security of these frameworks in order to give learners secure MCL services [24]. They are inspired by this reality and provide a solution to deal with instances of rogue Dynamic Host Configuration Protocol (DHCP) servers, which can be exploited by attackers to give users wrong IP addresses and so allow communication lines.

5 APPLICATIONS IN MOBILE AND 5G/6G NETWORKS

It is essential to comprehend the 5G and 6G network roadmap in order to keep current with the most recent developments in mobile communication technology. These networks are predicted to transform the way of living, working, and studying; therefore, it's critical for businesses to comprehend and make investments in wireless technology. Recent studies indicate that 5G networks would be able to accommodate large connections with peak data rates exceeding 10 Gbps and a minimum data rate of 100 Mbps. 5G technology advances aim to provide fast data rates, minimal latency, and excellent reliability, which allow a range of applications, including cloud services, virtual reality, and augmented reality.

5.1 The Journey from 1G to 5G

Every successive generation of mobile technology brings with Along with a number of systemic changes in terms of applications, market prospects, and convergent sectors, it also brings with it new capabilities and requirements in terms of spectrum, equipment, and other supporting assets[25]. It is positioned to be the most significant addition to fixed-line choices to date and to be a very fast, huge, always-on/everywhere architecture. The main takeaway from 5G's late incubation and early deployment phases is that it radically alters digital networking and upends sectors that rely heavily on mobile devices.

5.2 Applications and Benefits of 5G

The evolution of 5G network development has produced a plethora of advantages and uses that have revolutionised sectors and enhanced user experiences. In addition to improving mobile broadband capabilities, ultra-low latency, and large machine-type communications, 5G has made a number of applications possible, including the Internet of Things, autonomous driving, virtual and augmented reality, remote surgery, and smart cities[26]. 6G networks make it possible to communicate more quickly and widely, to the point where the line separating the real and virtual worlds is blurred. As multiband ultrafast seamless networks and incredibly reliable data transmission systems have rapidly advanced, the current cellular network can support high traffic applications like AI, ML, DL, augmented reality, virtual reality, 3D media, the IoT, and the Internet of Nano-things.

6 LITERATURE REVIEW

This literature review explores recent developments in energy-efficient resource allocation, power management, microservice scheduling, federated learning, secure offloading, smart city optimization, with a focus on deep reinforcement learning methods, 5G edge integration, and adaptive frameworks to improve system performance and efficiency.

Dhatchayani et al., (2025) introduced an improved framework to maximize smart city infrastructure through joint use of 5G edge artificial intelligence with Adaptive Multi-Agent Reinforcement Learning (AMARL). A new system connects 5G edge computing to adaptive reinforcement learning agents which optimizes real-time choices for various urban domains including traffic regulation and energy networks alongside environmental detection and public security operations. The placement of AI models at 5G edge nodes cuts latency levels down by more than 80% thereby providing essential ultra-low response times for dynamic urban environments[27].

Hassan et al. (2024) The suggested MCVS scheduling technique takes into account mobile device time, cost, network, location, and central processing unit (CPU) power to train data in order to predict the utilisation rates of certain microservices for a workable task scheduling scheme. The microservice software architecture is famous for its scalability, flexibility, and independent deployment of distinct components. The success of the proposed approach is shown by many simulation results that use metrics for execution time, CPU use, and offloading. Comparing experimental results to existing approaches, the results show that training and task offloading phases, as well as training and testing learning rates are advantageous. It is less costly and energy-intensive to offload microservices in MCC using the proposed method. The providing of graphical results demonstrates the effectiveness of the suggested technique. When the proposed model is compared to the most advanced techniques, it attains an average of 0.18% CPU usage and 4.5% service offloading rate for an 80% service arrival rate[28].

Tan et al., (2023) minimising the cost of the FL system by taking into account the training nodes' mobility, processing power, and transmission capacity. For various node speed circumstances, provide an algorithm and a method, correspondingly. An technique that uses low-speed and stationary training nodes is based on Deep Reinforcement Learning (DRL). Nodes with high mobility are handled via a heuristic approach. According to simulation findings, the suggested methods efficiently choose the right training nodes and can cut system costs by up to 20%[29].

Ju et al., (2023) A deep reinforcement learning based joint secure offloading and resource allocation (SORA) scheme based on the physical layer security (PLS) technique and spectrum sharing architecture is proposed to improve the confidentiality and resource efficiency of multi-user VEC networks, where the VU offloading links share the frequency spectrum used by the V2V communication links. Wyner's wiretap coding technique may be applied to ensure that private information cannot be decoded by several mobile eavesdroppers and to achieve the proper secrecy rate[30].

Zhang, (2023) suggested a deep reinforcement learning-based resource allocation method that works. Numerical studies have demonstrated the effectiveness of approach for 5G base stations in terms of offloading and energy savings. Furthermore, renewable energy is becoming a more significant power source for mobile edge computing devices due to the high prices of grid power supply. However, it is extremely difficult to provide consumers with high-quality services while meeting the requirements of low latency due to the significant intermittency and unpredictability of renewable energy. Thus, the co-deployment of hybrid energy storage and edge servers at 5G base stations is described in this study. Additionally, considering the information and energy domains, provide a measure of the overall cost of services[31].

Xu and Ai (2022), In the millimeter-wave (mmWave) HSR systems with hybrid beamforming, suggest a novel experience-driven power allocation algorithm that can learn power decisions based on prior experience rather than an exact mathematical model, in a similar way to learning to drive. The recently developed multi-agent deep deterministic policy gradient (MADDPG) technique is used to do this, allowing the agent—the train's mobile relay—to independently learn power decisions based on historical data.[32].

Table 2 examines the literature review summary regarding Smart Power Allocation, encompassing Approaches, Key Findings, Challenges, and Limitations

Table 2: Summary of related work based on Smart Power Allocation in Mobile Systems Using Deep Learning

References	Approaches	Key Findings	Challenges	Limitations
Dhatchayani et al., (2025)	Joint use of 5G edge AI with Adaptive Multi-Agent Reinforcement Learning (AMARL)	Reduced latency by >80%; optimized traffic, energy, environment monitoring, and public security	Integration of multiple urban domains in real-time	Scalability across large-scale smart cities remains complex

Hassan et al., (2024)	MCVS scheduling algorithm for microservice task offloading considering device/network/CPU constraints	Improved service offloading by 4.5 percent and reduced CPU consumption by 0.18%; this resulted in cost savings and effective offloading.	Balancing between task scheduling and resource availability	Performance depends on accurate prediction of microservice usage
Tan et al., (2023)	Heuristic method for high-mobility nodes in FL; DRL-based approach for low-speed/stationary nodes	Reduced system cost by up to 20%; effective training node selection	Handling dynamic mobility scenarios in federated learning	Limited adaptability in ultra-fast mobility environments
Ju et al., (2023)	Spectrum sharing and DRL-based Secure Offloading and Resource Allocation (SORA) with PLS	Improved secrecy and resource efficiency in VEC networks; Wyner's coding ensures secure offloading	Protecting against mobile eavesdroppers in dynamic spectrum use	Additional overhead from implementing secure coding
Zhang, (2023)	DRL-based resource allocation with renewable energy and hybrid energy storage at 5G edge	Achieved efficient energy savings and cost reduction; addressed intermittency of renewables	Managing unpredictability of renewable energy for low-latency services	Dependence on renewable availability and hybrid storage deployment
Xu and Ai, (2022)	Experience-based MADDPG for power distribution in hybrid beamforming mmWave HSR systems	Learned power allocation decisions from past experience; suitable for high-speed trains	Reliable learning under fast-changing mmWave conditions	Requires large training data; adaptation delay in real-time

7 CONCLUSION AND FUTURE WORK

As mobile systems evolve to support a diverse range of services and applications, efficient power management has become a critical requirement. Deep learning techniques have shown remarkable potential in handling the complexity of modern mobile environments by enabling adaptive, data-driven power allocation strategies. By learning from real-time network and user behavior data, these models can achieve intelligent decision-making that balances performance with energy consumption. The reviewed research indicates strong progress in using deep neural networks—such as CNNs, DQNs, and RNNs—for dynamic power control. Their ability to operate in non-linear, high-dimensional spaces makes them well-suited for real-world wireless scenarios, where traditional models often fall short. Deep learning has demonstrated improved throughput, latency, and energy efficiency in various use cases, particularly when combined with edge computing and mobile cloud environments. Although these findings yield some promising results, there are still limitations that have to be overcome before deploying on a large scale is a possibility. The complexity of models, responsiveness in real-time, availability of data and limitations to hardware are still considerable obstacles. There is an increasing need for these models to be explainable and safe, as they are being integrated into critical mobile systems.

In future work, an adaptive and context-specific deep learning model tailored to dynamic environments, such as mmWave NOMA and mobile users, should be developed. Integration of real-time data updates, intelligent jamming-resisting, and mobility-sensitive algorithms can enormously boost the robustness of the system. Also, the development of quality-assured domain-specific datasets and the ability to explore them are essential.

REFERENCES

- [1] W. Ejaz, S. K. Sharma, S. Saadat, M. Naeem, A. Anpalagan, and N. A. Chughtai, "A comprehensive survey on resource allocation for CRAN in 5G and beyond networks," 2020. doi: 10.1016/j.jnca.2020.102638.
- [2] T. M. Fernández-Caramés, P. Fraga-Lamas, M. Suárez-Albela, and M. Vilar-Montesinos, "A fog computing and cloudlet based augmented reality system for the industry 4.0 shipyard," *Sensors (Switzerland)*, 2018, doi: 10.3390/s18061798.
- [3] H. Yu, H. Lee, and H. Jeon, "What is 5G? Emerging 5G mobile services and network requirements," *Sustain.*, 2017, doi: 10.3390/su9101848.
- [4] E. Abad-Segura, M. D. González-Zamar, J. C. Infante-Moro, and G. R. García, "Sustainable management of digital transformation in higher education: Global research trends," *Sustain.*, 2020, doi: 10.3390/su12052107.
- [5] G. J. Nalepa, K. Kutt, B. G. Zycka, P. Jemioło, and S. Bobek, "Analysis and use of the emotional context with wearable devices for games and intelligent assistants," *Sensors (Switzerland)*, 2019, doi: 10.3390/s19112509.
- [6] F. Boccardi, R. Heath, A. Lozano, T. L. Marzetta, and P. Popovski, "Five disruptive technology directions for 5G," *IEEE Commun. Mag.*, 2014, doi: 10.1109/MCOM.2014.6736746.
- [7] G. Marques, R. Pitarma, N. M. Garcia, and N. Pombo, "Internet of things architectures, technologies, applications, challenges, and future directions for enhanced living environments and healthcare systems: A review," 2019. doi:

- 10.3390/electronics8101081.
- [8] P. B. Patel, "Thermal Efficiency and Design Considerations in Liquid Cooling Systems," *Int. J. Eng. Sci. Math.*, vol. 10, no. 3, pp. 118–125, 2021.
- [9] M. M. Khan, S. Hossain, P. Mozumdar, S. Akter, and R. H. Ashique, "A review on machine learning and deep learning for various antenna design applications," *Heliyon*, vol. 8, no. 4, p. e09317, 2022, doi: 10.1016/j.heliyon.2022.e09317.
- [10] M. da Silva and J. Guerreiro, "On the 5G and Beyond," *Appl. Sci.*, vol. 10, p. 7091, 2020, doi: 10.3390/app10207091.
- [11] W. Hatcher and W. Yu, "A Survey of Deep Learning: Platforms, Applications and Emerging Research Trends," *IEEE Access*, vol. PP, p. 1, 2018, doi: 10.1109/ACCESS.2018.2830661.
- [12] D. U. Campos Delgado, J. M. Luna-Rivera, A. J. Rojas, and C. Gutierrez, "Power Allocation in Mobile Cellular Communication Under Multiplicative Noise and Interference Uncertainty," *IEEE Trans. Control Netw. Syst.*, vol. 4, p. 1, 2015, doi: 10.1109/TCNS.2015.2512323.
- [13] R. Meylani, "A Comparative Analysis of Traditional and Modern Approaches to Assessment and Evaluation in Education," *Bati Anadolu Eğitim Bilim. Derg.*, vol. 15, 2024, doi: 10.51460/baebd.1386737.
- [14] K. Jakobsen, M. Mikalsen, and G. Lilleng, "A literature review of smart technology domains with implications for research on smart rural communities," *Technol. Soc.*, vol. 75, p. 102397, 2023, doi: <https://doi.org/10.1016/j.techsoc.2023.102397>.
- [15] S. R. Doha and A. Abdelhadi, "Deep Learning in Wireless Communication Receiver: A Survey," pp. 1–16, 2025.
- [16] R. Patel, "Sustainability and Energy Management : Trends and Technologies for a Greener Industrial Future," *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 4, no. 1, pp. 886–898, 2024, doi: 10.48175/IJAR SCT-19200E.
- [17] K. O'Shea and R. Nash, "An Introduction to Convolutional Neural Networks," *ArXiv e-prints*, 2015.
- [18] M. Gaballa, M. Abbod, and A. Aldallal, "A Study on the Impact of Integrating Reinforcement Learning for Channel Prediction and Power Allocation Scheme in MISO-NOMA System," *Sensors*, vol. 23, no. 3, 2023, doi: 10.3390/s23031383.
- [19] Z. Elsaraf, F. A. Khan, and Q. Z. Ahmed, "Deep Learning Based Power Allocation Schemes in NOMA Systems: A Review," *2021 26th Int. Conf. Autom. Comput. Syst. Intell. through Autom. Comput. ICAC 2021*, pp. 1–15, 2021, doi: 10.23919/ICAC50006.2021.9594173.
- [20] N. Kaur, "Robustness and Security in Deep Learning: Adversarial Attacks and Countermeasures," *J. Electr. Syst.*, vol. 20, pp. 1250–1257, 2024, doi: 10.52783/jes.1436.
- [21] Y. Wang *et al.*, "A survey on deploying mobile deep learning applications: A systemic and technical perspective," *Digit. Commun. Networks*, vol. 8, no. 1, pp. 1–17, 2022, doi: <https://doi.org/10.1016/j.dcan.2021.06.001>.
- [22] M. T R, S. Singh, V. Srivastav, H. Kalra, T. rajan, and G. Yadav, "Adaptive Modeling for Real-Time Data Analysis with Machine Learning," 2023, pp. 1–6. doi: 10.1109/SMARTGENCON60755.2023.10442430.
- [23] G. Kambourakis, "Security and privacy in m-learning and beyond: Challenges and state-of-the-art," *Int. J. U-and E-Service, Sci. Technol.*, vol. 6, pp. 67–84, 2013.
- [24] P. B. Patel, "Strategic Maintenance And Criticality Analysis For Maximizing Plant Productivity," *Int. J. Eng. Sci. Math.*, vol. 12, no. 1, 2023.
- [25] S. Mendonça, B. Damásio, L. Charlita de Freitas, L. Oliveira, M. Cichy, and A. Nicita, "The rise of 5G technologies and systems: A quantitative analysis of knowledge production," *Telecomm. Policy*, vol. 46, no. 4, 2022, doi: 10.1016/j.telpol.2022.102327.
- [26] T. Agboola, J. Adegede, T. Omomule, O. Oyeniran, and L. Aina, "A Review Of Mobile Networks: Evolution From 5G TO 6G," *Comput. Eng. Intell. Syst.*, vol. 15, pp. 49–61, 2024, doi: 10.7176/CEIS/15-1-06.
- [27] K. Dhatchayani, R. Shubavathy, G. R. Reshma, A. E. A, D. Sundar, and D. Vezhaventhan, "Optimizing Smart City Infrastructure Using 5G Edge AI with Adaptive Multi-Agent Reinforcement Learning," in *2025 International Conference on Visual Analytics and Data Visualization (ICVADV)*, 2025, pp. 1286–1292. doi: 10.1109/ICVADV63329.2025.10961787.
- [28] M. U. Hassan, A. A. Al-Awady, A. Ali, M. M. Iqbal, M. Akram, and H. Jamil, "Smart Resource Allocation in Mobile Cloud Next-Generation Network (NGN) Orchestration with Context-Aware Data and Machine Learning for the Cost Optimization of Microservice Applications," *Sensors*, 2024, doi: 10.3390/s24030865.
- [29] C. Tan *et al.*, "Self-adaptive and Efficient Training Node Selection for Federated Learning in B5G/6G Edge Network," in *NOMS 2023-2023 IEEE/IFIP Network Operations and Management Symposium*, 2023, pp. 1–5. doi: 10.1109/NOMS56928.2023.10154458.
- [30] Y. Ju *et al.*, "Joint Secure Offloading and Resource Allocation for Vehicular Edge Computing Network: A Multi-Agent Deep Reinforcement Learning Approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 5, pp. 5555–5569, 2023, doi: 10.1109/TITS.2023.3242997.
- [31] M. Zhang, "Deep Reinforcement Learning Based Resource Allocation for Renewable-Powered 5G Base Station," in *2023 IEEE 5th International Conference on Power, Intelligent Computing and Systems, ICPICS 2023*, 2023. doi: 10.1109/ICPICS58376.2023.10235441.
- [32] J. Xu and B. Ai, "Experience-Driven Power Allocation Using Multi-Agent Deep Reinforcement Learning for Millimeter-Wave High-Speed Railway Systems," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 6, pp. 5490–5500, 2022, doi: 10.1109/TITS.2021.3054511.