Towards Green Future Cellular Network in Nigeria: Artificial Intelligence Approach

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ABSTRACT

For the purpose of lowering energy costs and minimizing the use of fossil fuels, the information sector has traditionally targeted green communications. Without a doubt, the number of linked terminals and the amount of network equipment will continue to grow dramatically in the current 5G and next 6G eras, driving up energy costs. It is becoming more and more crucial to promote the advancement of green communications. But there is no denying that 6G will come with a host of new and more demanding specifications for intelligence, security, flexibility, and Quality of Service (QoS), all of which will make it harder to increase energy efficiency. Additionally, the dynamic energy harvesting process which is expected to be widely used in 6G makes network administration and power control even more difficult. Artificial Intelligence (AI) has been widely regarded as the sole way to handle these issues and minimize the need for human intervention. In order to reduce energy consumption, increase energy efficiency, and control energy harvesting in many communication settings, academia and industry have undertaken a great deal of research. The primary factors for green communications are discussed in this study, along with a review of relevant studies on AI-based green communications. This work focus is on the application of AI approaches to network management and energy efficiency enhancement as we move toward a greener future. The ways in which advanced Deep Learning (DL) and other Machine Learning (ML) approaches can work in tandem with traditional AI techniques and mathematical models to lower algorithm complexity and increase accuracy rates in future communication beyond 5G was examined. Lastly, the current concerns and unresolved research questions related to AI Techniques for future green communication was presented. Relative research towards green cellular network communication (CNC) was presented and it shows that Heuristic algorithms are widely used. Both flexibility and efficiency can be increased, using Heuristic algorithms and machine learning (ML) together. Also, Reinforcement Learning (RL) and Deep reinforcement learning (DRL) approaches helps to achieve the best policy for resource allocation and power control. However, the training process is challenged by the extraordinarily large action space resulted from nature of the metrics taken into consideration.

Keywords: *Green communication, AI, ML, Terahertz, 6G, CNC, MIMO, Energy Efficiency.*

1. INTRODUCTION

5G has been launched for high-throughput services in some countries, while researchers are exploring 6G. However, 5G Base Stations and mobile devices consume more energy than 4G, mainly due to Power Amplification in MIMO antennas and data processing, despite a drop in energy consumption per unit of data (Letaief *et al.,* 2019; Saad *et al*., 2020).

The increasing energy cost in 5G is significant, as the number of required 5G BSs is at least four times higher than 4G for the same coverage, with the ICT industry accounting for nearly 20% of total electricity consumption and annual rate of 6% to 9% (Mao *et al*., 2022).

What energy-related circumstances will accompany 6G then? As is currently known, 6G is anticipated to increase the number of bands to 1,000 times the frequency in Terahertz (THz) throughput enhancement based on 5G (Letaief *et al*., 2019). Given the top transmission range's limit is now 10m of THz spectrum instead of 100m of millimeter wave (mmWave). Small Base Stations (SBSs) with THz capabilities, are limited to cover a 100m^2 area (Matti & Kari, 2019) indicating that the necessary number of BSs is going to rise dramatically. In addition, aside from the utilization of communication, computation and content supply services will progressively move from local devices to servers on the cloud and edge (Jyothirmai *et al.,* 2023; Haibeh *et al*., 2022). These are the primary components of the energy usage for ICT. Furthermore, using Artificial Intelligence (AI) techniques to provide automated network management, personalized and context-aware information transmissions, and personalized services is another essential paradigm (Letaief *et al*., 2019; Sivabalaselvamani, 2020; Aouedi *et al*., 2022). Energy consumption will soar as a result of the expanding ICT infrastructure, the explosion of data, and the AI-based services (Thiruvasagam *et al*., 2021).

Two main areas of study have been undertaken by academia and industry to mitigate the increasing energy load associated with 6G: the first involves implementing energy harvesting techniques (Mao *et al.,* 2019; Chu *et al.,* 2018) and the second involves creating energy-efficient network management algorithms (Bashar et al., 2020; Vallero *et al.,* 2021). Energy harvesting devices and simultaneous wireless information and power transmission (SWIPT) have been widely used to convert different forms of sustainable energy into power for ICT equipment.

Large-scale iteration-based mathematical models have been proposed for energy-efficient network management in order to maximize the bit-per-Joule (Liu & Deng, 2020; Williams *et al.,* 2021; Ogbebor *et al.,* 2020). Meanwhile, popular Machine Learning (ML) techniques and conventional heuristic algorithms have been adopted (Chang *et al.,* 2020; Mao *et al.,* 2021) by AI techniques to streamline the traditional mathematical iteration process. However, these conventional techniques will not be effective due to the varied and dynamic service requirements to be satisfied by future green communications.

Modern machine learning approaches like Deep Learning (DL) have been extensively researched in order to solve this problem (Xiao *et al.,* 2020; Zhang *et al.,* 2020; Gong *et al.,* 2020). Furthermore, several alternative methods such as Intelligent Reflecting Surface (IRS) which is energy-efficient, has drawn more and more attention (Hashida *et al.,* 2020; Zeng *et al.,* 2020; Zhang *et al*., 2020; Zhu *et al.,* 2021).

In this paper, focus is on AI models including the traditional heuristic algorithms, traditional ML, and the state of the art DL to alleviate energy cost and improve energy efficiency in Cellular Network Communications (CNC). How the AI models are adopted for this communication scenario is discussed briefly. To introduce the green communication-related works clearly, we give some introductions to several 6G Enablers including the THz communications, Space-Air Ground Integrated Networks (SAGINs), energy harvesting, and AI models commonly utilized in existing works. Thus, the contributions can be summarized as below:

- The key techniques of future wireless communication as well as the AI approaches which have been studied in existing green communication related research are introduced in this article.
- We analyse the green ICT systems from not only the communication perspective, but also the viewpoint of computation. And this survey covers the most promising 6G network scenarios, including THz-enabled cellular networks, SAGINs, and IoTs.
- We envision the challenges of AI-based 6G green communications including the overwhelming computation overhead, security issues, and practical deployment.

The rest of this work is summaries as follows: Section 2 presents existing survey works on green communications and research issues in this article. In section 3 several 6G key enablers and the commonly utilized AI methods for green communications are explained. Section 4 explained related research works on green Cellular Network Communications (CNC). The envisioned future research directions were presented in section 5. The article was concluded in section 6.

2. REVIEW ON EXISTING SURVEYS AND RESEARCH ISSUES TOWARDS GREEN 6G

2.1. Review of Existing Survey Towards Green Communication

For over a decade, the field of green communications has garnered the interest of researchers. Table II enumerates the relevant survey articles in this regard. It is discovered that (Liu & Deng, 2020; Pratama *et al*., 2021) concentrated on optical communication networks and provide thorough overviews of the studies on reducing energy usage. In the context of cellular networks, (Ogbebor *et al.,* 2020) presents the literature on the enhancement of physical layer energy efficiency, whereas (David *et al*., 2021; Salahdine *et al*., 2021) focused on the access layer. Additionally, (Salahdine *et al.,* 2021) provides comprehensive modelling techniques for energy efficiency and power usage.

The energy-efficient solutions for the major 5G technologies density networks, massive MIMO, and visible light communications (VLC) are methodically addressed in reference (Jayarajan *et al.,* 2021). The 3G, 4G, and 5G systems, wired and wireless components are covered by these research projects. Numerous studies have examined the energy efficiency concerns taking into account the new technologies in light of the anticipated improvements to 6G communications systems, including SAGIN, AI, and Non-Orthogonal Multiple Access (NOMA) (Liao et al., 2021; Han et al., 2020), which will be covered in this article.

Another key 6G paradigm is energy harvesting, although this subject has been covered in several studies (Williams *et al.,* 2021; Yin *et al*., 2020) (P. Sharma & Singh, 2023; Ahmad *et al*., 2021; Perera et *al.,* 2016). Even though, this technique can significantly minimize the energy demand from the electric grid, the dynamics of harvesting electricity challenge the network stability. AI methods have been effectively assessed to maximize the effectiveness of systems with harvesting capabilities (Mao *et al*., 2019; Chu *et al*., 2018). Furthermore, a lot of analysis has been done on the energy challenges, including coding (Chen *et al*., 2019), beamforming, and security (Hu *et al.,* 2019). In the future, the diversified service needs for 6G consumers necessitate taking into account many assessment measures, in which case AI will be the most effective resolution (Redhu & Hegde, 2020; Al-Hilo *et al.,* 2021).

Furthermore, a greater deployment of edge, fog, and cloud servers is anticipated to provide real-time computing and caching services (Rodrigues *et al.,* 2020; Venanzi *et al.,* 2019; Bellavista *et al*., 2020). The information transmission process is also a part of the computing and content caching services, therefore energy-saving techniques should take both the computation caching and communication components into account.

2.2. Research Issues Towards 6G

After going over the surveys that are now available on energy-efficient communications, it can be observed, even with the promised 6G technologies, there is still a need for a thorough examination of green communications. In this piece, we examine the most effective AI methods for green communications and how they interact with the new 6G paradigms to promote green communications. This article covers the research works on CNC.

2.2.1 Cellular Network Communications: The deployment and work state scheduling of BSs are the primary subjects of relevant research on green CNC as BSs account for the bulk of energy consumption for cellular networks. Because user association may be changed to switch off the BSs when not in use, it is also very important. Power control and resource allocation for operating base stations (BSs) should be examined to enhance energy efficiency, and energy harvesting technology has been contemplated to lower the demand for grid electricity. However, because 6G networks will coexist alongside 4G and 5G, management will be more difficult due to the hierarchical structure, varied base stations, and diversified spectrum resources.

Furthermore, the traffic, user, and collected energy dynamics will cause the BSs reconfiguration on a regular basis. The development of AI models for power control issues will be hampered by the unknown Channel State Information (CSI), severe interference, and large solution space.

3. Overview of 6G Enablers and AI Methods for Green Communication

3.1. Several 6G Enablers

In this section, THz communications, SAGINs, and energy harvesting are briefly introduced. As the work focuses more on the development of AI models, a simple introduction to AI-based communications is also given.

1) Terahertz Communications: 6G aims to provide hyper-fast links with per link peak throughput exceeding Tbps, requiring wider bandwidth found in sub-THz and THz bands (Matti & Kari, 2019). THz communications can achieve Tbps throughput and end-to-end latency, but their link distance reduces to less than 10 meters, requiring an exponential increase in Base Stations (BSs) for seamless coverage, resulting in extreme energy costs (Letaief *et al*., 2019). Green deployment and management of 6G BSs should be prioritized to alleviate energy overhead.

2) Space-Air-Ground Integrated Networks: Satellites and flying aircraft are being used to construct Satellite-Assisted Global Infrastructures (SAGINs) in remote areas, including space, sky, sea, and terrestrial areas. These systems offer diverse services with different quality and channel conditions, allowing users to choose energy-efficient methods. However, these heterogeneous communication systems increase network management and performance optimization difficulties (Zhou *et al*., 2020; Lopez *et al*., 2020; Qiu *et al.,* 2019).

3) Energy Harvesting: Wireless charging techniques are expected to lead to widespread adoption of energy harvesting technology in 6G (Mao *et al.,* 2020). This technology can utilize renewable and non-renewable sources like vibrations and RF signals (Draskovic & Thiele, 2021). Renewable energy harvesting reduces communication system dependence on electric power (Temesgene *et al.,* 2020; Li *et al*., 2018) while non-renewable energy harvesting improves efficiency by utilizing wasted signals (Perera *et al.,* 2016) (Wanmei *et al.,* 2019). However, these techniques increase network uncertainties, necessitating the development of powerful methods to predict available energy (Perera *et al*., 2016) (Chu *et al.,* 2018).

4) AI-Based Communications: Besides the applications in image classification (Li *et al*., 2020), natural language processing, and game (Boulianne, 2020), AI techniques have been widely studied to optimize the network performance (Zhao *et al.,* 2023), while green communication is an important application. AI has been confirmed as an important paradigm for 6G to realize the network automatic management (Zhao *et al.,* 2023). Cooperation between several areas is necessary for future green network management, including resource allocation, network design, and implementation. Additionally, there are emerging trends in the direction of smarter communication management.

3.2. Artificial Intelligence (AI) Techniques for Green Communications

A. Traditional AI Algorithms

Artificial Intelligence (AI) techniques for green communications can be categorized into three groups: Heuristic algorithms, traditional machine learning methods, and Deep learning methods (Wu, 2021). While some ML methods belong to heuristic algorithms like Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), for clear explanations non-data-based heuristic models such as: Genetic algorithm, Ant colony and particle swarm are considered. The former uses online iteration-based search for optimal solutions, while the latter constructs and trains models with large amounts of data for experience accumulation.

1. Heuristic Algorithms: Heuristic algorithms tackle the NP-hard problem by finding a suitable solution within a limited time frame. They use shortcuts and are faster than greedy search methods, but sacrifice accuracy or near-global optimum. The shortcut methods vary among different heuristic algorithms including the Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Genetic Algorithm (GA).

Particle Swarm Optimization involves particles moving around a search-space based on their positions and velocities (Shami et al., 2022). Optimal solution based on improved position is influenced by best and known position in an iteration. The method is suitable for discrete processes (Houssein et al., 2021) and has been used to optimize edge server deployment (Gad, 2022) and Virtual Machines placement for energy efficiency. However, it is easy to fall into the local optimum and has a low convergence rate.

Ant Colony Optimization inspired by ants' search behavior, is a method that uses swarm intelligence to find the optimal route through simulating revolutions (Fidanova, 2021). This method has been widely studied for improving energy efficiency in network applications like routing (Maheshwari et al., 2021), resource allocation (Liao et al., 2017), and server deployment (Liu et al., 2018).

Genetic Algorithm is a method in evolutionary biology, abstracts candidate solutions as chromosomes or phenotypes, with crossovers causing new generations based on fitness with a certain probability (Dai & Zhang, 2020). It has been used for designing cellular networks and optimizing edge server deployment (Zhang et al., 2019). GA is easy to converge but cannot guarantee global optimum and relies on parameter selection.

I. Traditional Machine Learning: Numerous machine learning algorithms have been created as a data-driven method and used into numerous network performance improvement strategies (Rodrigues et al., 2020), (Abbasi et al., 2021), and (Bian et al., 2022). Three classic machine learning methods are the subject of this section: regression analysis (Skiera et al., 2022), support vector machines, and K-means clustering which are frequently employed in Green Communications (Mao et al., 2022).

Regression Analysis: Regression analysis is a method used to analyze the relationship between parameters, often used to map input parameters to output results. It has been used for predicting future traffic changes and determining energy-efficient transmission schemes, resource allocation, and computation offloading (Vallero *et al.,* 2021; Kwan *et al.,* 2020).

Support Vector Machine is a supervised learning model used for classification and regression analysis, using orthogonal vectors to define hyperplanes to separate training data points. This has been used in green communication management for user association (Debnath *et al.*, 2022) and computation offloading (Wang *et al*., 2021).

K-means Clustering is unsupervised learning technique that partitions multiple observations into clusters, assigning each to the nearest center based on cost function. This is efficient for energy savings (Zhang, *et al*., 2020) and optimizing cloudlet placement (Asghari & Sohrabi, 2024).

B. Deep Learning

The development of machine learning training strategies (Xiao *et al*., 2020; S. Dong *et al*., 2021) has made it possible for deep neural networks (NNs) to achieve noticeably higher prediction accuracy rates. Furthermore, supervised learning, unsupervised learning, and reinforcement learning (RL) are the three training methods that DL inherits from classical machine learning techniques. DL is widely applied in many areas (Abbasi *et al*., 2021), basic overviews of DL model creation and Deep reinforcement learning (DRL) are discussed.

Development of Deep Learning Models: Most current machine learning models are based on Artificial Neural Networks (ANNs), which are composed of interconnected artificial neurons that model biological brain neurons (Yang & Wang, 2020). The final output of each ANN depends on input signals, non-linear functions, and edge weights. This has witnessed recent developments which include: increased number of layers, advanced training algorithms and hardware for complex scenarios and overwhelming humans in applications like board games (Xiao *et al*., 2020). Modern ANNs, such as Convolutional Neural Networks (CNNs) (Chaturvedi *et al*., 2020), multiple ANNs such as the Generative Adversarial Network (GAN) (Gui *et al*., 2023), and Actor-Critic method (Zahavy *et al*., 2020) has been recently developed.

Deep Reinforcement Learning is a dynamic learning model that consists of an environment, an agent, state space, action space, and reward (Li, 2023). The study of complex problems often leads to a large number of states and potential actions, making the Q-value table impossible. To address this, Deep reinforcement learning (DRL) models are adopted to map states to corresponding actions, enabling agents to generalize values of previously unknown or partial states (Li, 2023). DRL has gained attention for improving energy efficiency through optimization of BS management (Temesgene *et al.,* 2021), resource allocation (Chaieb *et al.,* 2023), power control (Zhang & Liang, 2021), and computation offloading (Gong *et al*., 2020).

C. Emerging Training Strategies

Along with the creation of DL models, new training approaches have a significant impact on computation performance and accuracy rate. Concentration is mainly on two AI training methodologies in this section: federated learning and transfer learning.

Federated Learning is a decentralized method that uses distributed servers or devices to train and test AI models with local data (Bellavista *et al*., 2021). This cooperative training method efficiently uses idle edge computation resources, reducing central controller consumption and communication overhead (Dong *et al.,* 2020; Wang *et al.,* 2021; Shen et al., 2019).

Transfer Learning is a machine learning method that uses a built-in knowledge system to solve related problems (Niu *et al*., 2020). This approach is widely used in network changes due to mobility (Dong &

She, 2020). However, balance between training and performance requires further research.

Summarily, the main components of 6G will include technologies like AI, SAGIN, energy harvesting, and THz communications, a variety of AI models and methodologies have been created, varying in complexity and performance. The performance of 6G may be enhanced by using both advanced deep learning techniques and conventional AI methods, contingent on the complexity and requirements of the service. In this part, we primarily introduce the most popular and promising AI models and methodologies. A few AI methods have also been applied in various research projects, such as random forest, quantum ML, and imitation learning (Wang et al., 2020). Additionally, some RL techniques, such as fake learning and regret learning (Alharin et al., 2020), may be taken into account to increase efficiency.

4. CELLULAR NETWORK COMMUNICATIONS

The radio access component and the core component of cellular networks consume the most energy (Salahdine et al., 2021). Furthermore, research shows that over half of the energy used is accounted for by BSs, of which 50% to 80% is used for the power amplifier and feeder. Thus, BSs are the primary focus of green communication research for cellular networks. The 6G era's increased use of the frequency range to sub-THz and THz results in a further reduction in the coverage of a single base station (BS) (Fadlullah & Kato, 2022), an exponential rise in the number of BSs needed, which increases energy consumption.

4.1. Power Consumption and Energy Efficiency of Cellular Networks

Radio Access Network (RAN) component, which is made up of access terminals and base stations is considered in this work. We offer the "bit-per-Joul" metric to quantify energy efficiency for both access terminals and base stations, as well as the modeling of BSs' power usage.

Power Consumption Modeling of BSs: A BS's power consumption comprises four components: power supply, signal processing, air conditioning, and power amplifier (Salahdine et al., 2021), with some constant at sleep and idle states, and others influenced by workload. The Energy consumption can be given as (Wang et al., 2019):

$$P_{BS} = P_{SLP} + I_{BS}(P_{ADD} + \eta P_{TX}), \tag{1}$$

where:

P_{BS} denote the total power consumption of the BS,

P_{TX} is the maximum transmission power consumption of the BS,

$\eta \in [0, 1]$ denotes the usage rate,

P_{SLP} is the constant power consumption to sustain the basic functions in the sleep mode,

P_{ADD} denotes the additional constant power for computation, backhaul communication, and power supply in the active mode.

I_{BS} is a binary parameter representing whether the BS is active or sleep.

According to (1), reduced energy is achieved through intelligent component switching. For multi-tier heterogeneous BSs with THz band (Dai & Zhang, 2020), BS deployment, management, user association, and resource allocation are the techniques for reducing consumed energy.

Energy Efficiency Measurement: Energy efficiency measures performance in cellular networks by comparing transmission rate and power consumption in bits per-Joule. In this work, a multi-cell interference network with multiple single-antenna UEs and several multi-antenna BSs is considered. The same spectrum resource is multiplex among the cells. If one UE's transmission power and the channel gain to the corresponding BS are Pu and Gu, respectively, the maximum uplink transmission rate can be calculated as:

$$R_u = B\log\left(1 + \frac{G_u P_u}{N+I}\right), \tag{2}$$

Where R_u is the maximum transmission rate of the considered UE's uplink, B is the assigned bandwidth, N and I denote the noise and interference on the utilized channel, respectively.

Assuming μ is the inefficiency of power amplifier of considered UEs, P_{u_0} is the static power consumption. The energy efficiency can be calculated as below:

$$EE_u = \frac{R_u}{\mu P_u + P_{u_0}} \tag{3}$$

Equations (2) and (3) reveal that energy efficiency is influenced by parameters like bandwidth, channel gain, transmission power, and interference, while noise and static power consumption remain constant. Optimizing resource allocation is crucial for improved efficiency.

4.2. Network BS Management

The significant loss of THz radio signals in 6G BSs leads to limited coverage and increased energy consumption (Letaief et al., 2019). To reduce energy consumption and improve efficiency, BS deployment policy, workload management, and user association are attractive directions, focusing on minimizing the number and transmit power of working BSs.

BS Deployment: BS deployment significantly impacts communication performance and energy consumption during network construction. Despite manual selection based on population density (Jiang *et al.,* 2020), increasing dynamics, propagation characteristics, complex physical surroundings, and climates prompt researchers and operators to consider efficient, automatic strategies.

Dai and Zhang's research proposes a multi-objective GA approach to reduce the number of deployed BSs (Dai & Zhang, 2020). They extract key features determining Received Signal Strength (RSS) strength and use multiple machines learning models, including KNN (Bian et al., 2022), random forest, SVM, and Multi-Layer Perceptron, to map the relationship between these features and RSS values. Simulation results show MLP outperforms other ML models in mean absolute error (MAE). And the coverage rate is improved by 18.5% compared with real-world deployment.

Heuristic algorithms find solutions with low complexity, while machine learning models increase efficiency. This hybrid solution could be considered for future 6G, but the heuristic algorithm aims for a good solution within limited time, it can easily fall into the local optimum. The increasing variables in 6G systems, due to diversified service requirements, may affect the performance of heuristic models, necessitating the study of more efficient heuristic algorithms and advanced machine learning models to address these limitations.

Work State Scheduling: Network traffic changes due to user mobility can be managed by scheduling multi-tier BSs to switch on and off, reducing energy consumption. Adjusting user association information when BS work state changes ensures a qualified connection, requiring careful scheduling to minimize energy consumption and meet QoS requirements.

Traffic data and historical experience can be used to design BS switch policies (Sharma et al., 2017; Sharma et al., 2019). This method is easy, but potential QoS deterioration is a concern. To alleviate the concern, (Gao et al., 2020) compare traffic prediction rates, speed, and complexity of various machine learning models, including ARIMA, prophet, random forest, LSTM, and ensemble learning. The predictions are used to calculate energy efficiency, by BSs turned off comparing key performance indicator (KPI) with a predefined threshold.

Similarly, (Kim et al., 2021) use dense and RNN neural networks to predict future traffic of Small Base Stations (SBSs) based on previous trace data. The authors define a threshold to decide whether SBS should be switched off or kept on. Another strategy uses traffic trace to predict BS switching schemes. Simulation results show energy consumption reduction of 63% and satisfaction of over 99.9% of requests.

The above scenarios only considered two work states, (Yang et al., 2020) study the switching policy for multi-sleep-level-enabled Base Stations (BSs) in a two-tier cellular network using machine learning techniques. They use a SVM regression model to predict vacation period and operation time of SBSs based on historical network traffic profiles. The results are analyzed along with energy consumption and latency to determine the best sleep level for SBSs. The SVM used in the paper can be replaced by other regression models. The supervised learning-based approach is efficient for periodic traffic changes, but online learning may improve training accuracy rate with sacrificing convergence speed for dynamic traffic.

Moreover, researchers have combined RL and transfer learning to enhance flexibility and accelerate convergence. (Sharma et al., 2019) use RL agents to select BS work modes for system power minimization based on traffic patterns, transfer learning that uses past learning experiences to accelerate the learning process was exploited. To address QoS issue, the RL model's cost function is defined as an adjustable combination of energy consumption and service delay, instead of just energy consumption. Consequently, the proposal reduces energy consumption and ensures diverse QoS requirements. Additionally (Zahavy *et al.*, 2020) uses transfer learning to accelerate the convergence of the Actor Critic (AC) model. Similar research (Zhang, et al., 2020) uses RL and transfer learning to design BS switching policy, transferring spectrum assignment knowledge to user association process.

In (Liu et al., 2018), the BS switching strategy was also designed using the Deep Q-learning (DQL) approach, taking into account the network traffic. Unlike (Sharma et al., 2017;Sharma et al., 2019), which make use of the traffic pattern directly, The authors propose a traffic modeling module to predict traffic belief states in an Interrupted Possion Process (Ramanathan & Varadharajan, 2023). The Deep Q-network (DQN) decides sleeping policy based on the module's output. The proposed model is suitable for BSs with different traffic patterns, as stable parameters are stored separately in a separate network to prevent training oscillations and divergence, and adaptive reward scaling is applied to match network outputs.

(Panahi et al., 2018) propose a Fuzzy Q-learning (FQL) algorithm to address the QoS sacrifice caused by switching off BS in low usage for D2D based Heterogenous network. The FQL algorithm combines Q-learning and Fuzzy Interference System (FIS) (Panahi & Ohtsuki, 2014) to map the relationship between input energy efficiency, service success probability, and switching policy. The E-greedy algorithm explores and exploits potential switch on/off policies until convergence. After each state transition process, Macro Base Stations (MBSs) and Femto Base Stations (FBSs) receive the overall shared reward determined by the central entity, using it to update the Q value to avoid local optimization.

(Lee *et al.*, 2020), explore QL-based joint cell activation and user association for load balancing and energy saving. Each BS is treated as an agent, with state and action as current activation variables and mode respectively. A user association scheme is found by relaxing the load balancing problem to a convex problem. The Q-value based on heterogeneous network power consumption is calculated to evaluate the pair of BS activation and user association scheme. The reward or cost in reinforcement learning-based models (Yang *et al.*, 2020; Lee *et al*., 2020) is typically a weighted sum of energy consumption and QoS.

User Association Policy: The QoS deteriorates much more when neighboring operational BSs are overworked due to the idle BSs being switched to sleep or off mode. Studies have been conducted on AI-based user association systems to find a balance between energy efficiency and quality of service.

Zhang et al., (2020) use the QL technique to optimize user offloading in multi-tier Ultra Dense Networks (UDNs) to reduce energy consumption and improve network throughput. In the model, part of connected users can be offloaded to neighbour SBS or MBS, allowing idle SBS to sleep or off, while overloaded SBS can alleviate service provision. The reward function considers energy efficiency, throughput, and load difference among cells, while the mean normalization method is used to eliminate sample differences.

The authors of (Wang et al., 2019b) use game theory and RL technique to solve user association and Orthogonal Frequency Division Multiple Access (OFDMA) tile assignment. Each player is treated as a player to choose a heterogeneous NodeB (hgNB) considering potential profit and effects on other players similar to the reward function in (Zhang *et al.*, 2020). They propose two RL approaches to intelligently guide the search: the regret learning-based algorithm and the fictitious play-based algorithm.

Similar to the proposed traffic-aware work state scheduling (Sharma et al., 2017; Sharma et al., 2019; Kim et al., 2021; Gao et al., 2020; Wang et al., 2019) use machine learning techniques to predict potential traffic bursts and conduct traffic-aware vehicle association. The proposed architecture involves each Access Point (AP) performing independent traffic prediction, while the central coordinator conducts global traffic balance. The central coordinator can proactively update BS configurations to change user association information, allowing some BSs to prepare for traffic bursts and others to switch to off mode.

4.3. BS Power Control

According to Equation (3), transmit power control influences transmission rate, it is essential to increase system energy efficiency. The basic power management issue as well as the power control for the super massive Multiple-Input Multiple-Output (MIMO), Non-Orthogonal Multiple Access (NOMA), and beamforming technologies, which will be key approaches in future wireless communication (Letaief *et al.,* 2019) will be address.

General Power Control: The received SINR at the intended receivers and user interference for users in adjacent cells are both impacted by the transmit power of BSs. Thus, through transmit power management, interference mitigation and energy consumption optimization are simultaneously taken into account. (Li *et al.*, 2021) use the RL technique to optimize transmit power to reduce interference in neighbouring cells based on received SINR and user density. They assume each target base station (BS) has a defined utility based on SINR, energy consumption, and interference to non-served users. The Q-value is then defined to measure the overall performance of the transmit power level. The E-greedy policy is applied to determine the optimal transmit power level, resulting in reduced energy consumption and improved network throughput. In (Xiao *et al.,* 2020), the authors propose a DRL-based CNN model to map network states, including SINR, user density, and channel conditions, to transmit power levels. It offers an advantage in reducing interference.

(Dong *et al.,* 2020) use Fully-connected NN (FNN) and cascaded NN to optimize transmit power and channel allocation to minimize network energy consumption. The paper highlights the benefits of transfer learning in reducing training overhead and accelerating the development of intelligent 6G systems, while also suggesting further research on the sacrifice of accuracy rate in different 6G applications.

(Matthiesen *et al.,* 2020) propose an improved Branch-and-Bound (BB)-based algorithm to optimize weighted sum energy efficiency in transmit power determination. The ANN can be trained offline with a large dataset generated by the BB-based algorithm, ensuring robust online transmit power calculations against mismatches between the training set and real dataset conditions.

(Qian *et al.,* 2020) study power allocation in a distributed antenna system using the KNN model to optimize spectrum efficiency and energy efficiency. The research aims to alleviate high computation overhead using AI, using KNN to map the relationship between user location and power allocation. Traditional methods are used to obtain data samples for KNN models, which are then copied to the test group after calculating Euclidean distance between users.

Zhang and Liang propose a multi-agent-shared-critic DRL method for power control in multi-layer HetNet. The power control for multi-layer HetNet is more complex and difficult to reach the global optimum. The method involves training an actor and target actor DNN for every BS, with a shared pair acting as the critic and target critic. To avoid local optimum involvement, the core network uses global experience to train the critic DNNs. Similarly, Li et al., (2021) combines graph theory and RL technique to dynamically cluster cells based on received SINR.

The extension of frequency bands to THz is causing propagation and penetration loss. To address this, future THz-enabled TBSs should be limited to 10 meters, suitable for 6G indoor network scenarios. Power control in home cellular scenarios should be studied to mitigate interference among networked devices. The authors in (Gao et al., 2016) propose QL-based distributed and hybrid power control strategies to optimize network performance in terms of throughput, energy efficiency, and user experience satisfaction. The state is the received SINR level and current transmit power level, while the action is the power level assigned to each resource block (RB).

Power Control in Beamforming: In densely populated locations, adaptive beamforming is a crucial technique that allows for highly directed broadcasts by adjusting the directionality of the antenna array. (Liu et al., 2020) use LSTM to extract spatial and temporal features of UE distributions from a history dataset and detect future hotspots. The hybrid beamforming optimizes power allocation and beamforming directions, reducing energy consumption.

(Du et al., 2019) optimize cell sleeping control and beamforming operation using DNN models. They model the power minimization problem using joint cell sleeping and coordinated beamforming, constrained by SINR and maximum power threshold. The numerical method generates training data for the DNN models achieving power savings and QoS demands.

(Zhou *et al*., 2020) use manifold learning and K-means method to cluster multi-cell users into regions and reduce complexity in massive MIMO operations. They use the maximum-minimum distance-based K-means method to reduce computation overhead and transform nonlinear high-dimensional channel coefficients into linear combinations of neighbourhood channel coefficients. This results in significant dimension reduction while maintaining the original geometric properties of the channel manifold. Beamforming and other network factors are jointly optimized to improve energy efficiency, such as relay operations. (Wang *et al*., 2019a) use the Deep Deterministic Policy Gradient (DRL) technique to enhance multi-antenna Hybrid AP (HAP) beamforming strategies and RF-powered relay operations. A hierarchical Deep Deterministic Policy Gradient (H-DDPG) model is proposed to select the relay mode and optimize parameters to maximize SINR. Simulations show that the H-DDPG significantly improves throughput and convergence speed compared to the model-free DDPG method.

Power Control in MIMO: Distributed massive MIMO systems use user-transmitted pilot sequences to estimate channel estimation, but pilot contamination from orthogonal sequences affects accuracy. To reduce contamination, power allocation to each pilot sequence is crucial.

(Xu et al., 2019) developed an unsupervised learning method to predict power allocation schemes based on large-scale channel fading coefficients. They used the Minimum Mean-Square Error (MMSE) channel estimator and a Deep Convolutional Neural Network (DCNN) with channel fading coefficients and power allocation as input and output. The authors also proposed a heuristic sub-optimal approach for data samples to train the DCNN model. Another similar research (Andrea et al., 2019) utilize the ANN to map from the users' positions or shadowing coefficients to the power allocation vector. The benefits of deep learning approaches over conventional mathematical models have been confirmed by each of these research studies. The authors propose intelligent power control to suppress attack motivation in MIMO transmitters (Nie et al., 2020), focusing on energy efficiency. They combine game theory and real-time learning (RL) to control the power of the transmitter, formulating a game model between the transmitter and malicious attacker.

The authors of (Dong *et al.,* 2018) and (Gao *et al*., 2017) use a CE-based algorithm to solve the hybrid procoding problem in mmWave massive MIMO systems. The probability distribution of the analog beamformer is updated and the "elite" beamformer with minimum transmit power is computed. The two papers' simulations confirm that a low-complexity, CE-based hybrid precoding strategy can increase the energy efficiency of large MIMO systems operating in millimeter waves.

In contrast to the previous study that concentrated on intelligent power regulation in large MIMO systems, the authors of (Kim et al., 2021) propose a DL-based user-aware antenna allocation strategy for massive MIMO systems. They use an LSTM model trained on real datasets to predict future user variations for massive MIMO-enabled BSs, similar to the applications of DL in traffic forecast. An ideal number of BS antennas is assigned to optimize energy efficiency based on the forecast findings.

Power Control in NOMA: In order to multiplex users on the same channel resource, the NOMA approach adds an additional power domain, which can increase resource efficiency and network capacity. As a result, it is generally accepted that the resources, such as power and channels, should be optimized in order to increase network performance. In (Chaieb et al., 2023), the authors use the DRL technique to reduce computation overhead in channel assignment, using each BS as an agent and the NOMA system as the environment. The derived system performance is used to define the reward function, and the proposed NN finds optimal channel assignments. The authors of (Yang et al., 2019) employ the DL technique to reduce computation overhead in conventional methods, training a supervised DNN with downlink channel gains as input and output.

(Zhang et al., 2020) propose DL-based radio resource management to enhance energy efficiency in NOMA networks. They analyze sub-channel and power allocation as in (Chaieb et al., 2023), user association, and two-tier networks, including MBSs and SBSs is considered. The input and output of the NNs are channel gains and allocation strategies. To optimize power allocation, the DNN is trained with labels generated by an iterative gradient algorithm.

In the THz MIMO-NOMA systems, THz transmission faces path spreading and molecular absorption loss, which can be addressed by implementing a clustering scheme to separate users into different clusters, enhancing channel quality, suppressing interference, and increasing SINR and transmission throughput. The authors of (Zhang et al., 2020) propose an enhanced K-means strategy for user clustering, overcoming fluctuation with initial clustering centers. The MSE analysis confirms improved convergence compared to the conventional K-means method, making it efficient for power control in NOMA-enabled multi-tier cellular networks. Moreover, more research should be done on K-means clustering and other unsupervised learning models to boost their efficiency as network increases and factors taken into account in 6G rise.

4.4. Renewable Energy-Based BS Management

Renewable energy sources are being explored to reduce reliance on the electrical grid, but their dynamics pose challenges in managing and operating cellular networks. In order to enhance network operations, AI approaches have been extensively investigated for tracking the dynamic harvesting source.

Predicting the harvesting power is the most straightforward way to maximize cellular network performance with renewable energy-enabled base stations. The authors of (Vallero et al., 2021) employ the Block Linear Regression (BLR), ANN, and LSTM to anticipate traffic in the case where BS is powered by a photovoltaic (PV) panel, battery, and power grid. The linear regression model is used to estimate the harvesting power and intelligently turned off underutilized base stations using the predicted findings.

(Temesgene *et al*., 2020) propose a distributed RL-based SBS switching strategy to balance network drop rate and energy consumption in two-tier cellular networks powered by the electricity grid and renewable solar energy. However, this method has limitations for system optimization. To alleviate this problem, The authors propose a layered learning optimization framework in (Miozzo et al., 2019), where each SBS decides switching schemes in a distributed intelligent manner, with a heuristic function defined and combined with the regular Q-value for optimal policy selection.

Li et al., (2018) propose a centralized method for managing work states of harvesting-enabled SBS using the Decision Tree Language (DRL). DQL outperforms traditional QL in terms of energy efficiency and delay, but the action space size exponentially increases with the number of SBSs, causing extensive explorations during training. To solve this problem, (Li et al., 2018) propose the DDPG model, which uses the AC algorithm, resulting in improved energy efficiency compared to DQN and QL methods.

Since batteries are typically used to store the energy generated by renewable energy-enabled base stations, optimizing battery management may help increase energy efficiency. The authors of (Mendil *et al.,* 2018) propose FQL-based power management, combining QL and fuzzy inference system (FIS) (Busoniu *et al.,* 2007) to reduce electricity costs and improve battery life. (Piovesan et al., 2020) compare imitation learning, QL, and DQL methods for designing SBS switching schemes considering energy constraints and sharing. The DQL model outperforms QL in terms of energy saving and system outage, making it suitable for highly-dense scenarios. (Wei *et al*., 2017) use policy gradient-based AC networks to solve user scheduling and resource allocation problems in a two-tier HetNet powered by solar and wind energy. The wireless fading channels and stochastically harvested renewable energy have the Markovian property (Simsek *et al*., 2014), allowing for optimization using DRL algorithms. Online training improves energy efficiency through numerical analysis.

It is clear from the aforementioned introductions that AI methods are effective in addressing the dynamics of the energy harvesting process. Furthermore, AI models may be used to improve the grid-powered BSs' switching schemes, user associations, power controls, and resource allocation for the next 6G BSs that are fuelled by diverse energy sources.

5. Open Research Issue

As the end terminals can be served by different BSs including the MBSs, SBSs, and TBSs in the multi-tier 6G HetNet, the heterogeneous hardware architectures and the mobility further complicate the green management. Optimizing user association policy requires resource allocation for energy savings. However, heterogeneity in BSs, end device mobility, and resource heterogeneity can cause changes in traffic demand and dynamic channel conditions. AI models can predict traffic demands, mobility patterns, and channel conditions, enabling network reconfigurations in advance.

Furthermore, future BSs is expected to be perform both computation/storage providers and energy source. AI models can be use to optimised the computation offloading and content caching policies. These are usually modelled as a non-convex problem, and further address by the RL or DRL techniques. The RL or DRL can find the global optimal solution and avoid the complex iteration process during the algorithm execution period.

Packet transmission is energy-consuming as it costs energy of transmitters, forwarders, and receivers. AI has been used to reduce energy consumption in various ways, including power control, resource allocation, routing policy design, relay, backscatter communication, and IRS-aided transmissions. However, limited research has focused on hybrid scenarios, making it crucial to focus on AI-based approaches to improve energy-efficient transmission in network scenarios with multiple communication manners.

To drive the development of green communications, various energy harvesting techniques will be utilized, which can be divided into different groups according to whether it is controllable and predictable. AI techniques can be used in scenarios involving uncontrollable but predictable energy groups and partially controllable energy groups. AI models can improve energy harvesting efficiency by mapping future harvesting power relationships and predicting network reconfiguration. They can also optimize power control and transmission scheduling in partially controllable RF energy harvesting techniques. AI can reduce wasted energy, share energy among devices, and balance RF harvesting and information transmission. Ambient backscattering is a promising technique for low power machines, and AI can optimize energy harvesting and information forwarding processes.

For the future AI-driven 6G, a new type of network threat may be the malicious data generated by the adversaries, which misleads AI models to reach a wrong result. AI models for green communications must be robust and sensitive to data security issues, as they may lead to widespread outages or low harvesting efficiency. Developing robust AI models and implementing data security standards and regulations are crucial for ensuring green communications and addressing potential privacy and business information concerns.

Current research focuses on network performance improvement for AI-based green communications, neglecting energy consumption for training and running models. This may lead to high complexity and energy-aggressive AI models. Minimizing training data and decreasing algorithm complexity is crucial for AI-based green communications, while balancing energy efficiency and network performance. Research on energy-efficient AI algorithms is limited, prompting further study on designing hardware for computation acceleration at low cost.

6. Conclusion

Relative research towards green CNC was presented and it shows that Heuristic algorithms are widely used and well-developed for optimizing business system setups, such as user association, work state scheduling, and deployment. Heuristic algorithms and machine learning (ML) together can increase both flexibility and efficiency. The best policy for resource allocation and power control may be found effectively using RL and DRL approaches. However, the training process is challenged by the extraordinarily large action space created by the continuous and numerous alternative combinations of the metrics taken into consideration, which calls for more work.

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