Migration Letters

Volume: 21, No: S6 (2024), pp. 788-796

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

A Multi-Objective Approach For Optimizing Energy Consumption In 6G Mobile Communication Networks

Sonia Aneesh[1*] and Alam N. Shaikh[2]

1

Abstract

The emergence of 6G mobile communication networks has led to a growing demand for sustainable energy solutions. This technical research paper investigates the energy consumption challenges faced by 6G networks that rely on battery-powered devices. The limited battery capacity of these devices poses a challenge in terms of reducing energy consumption and extending network lifetime. Our research aims to identify the optimal nodes for data transmission inorder to minimize energy consumption and maximize network lifetime in 6G networks. Furthermore, we take into account the societal responsibility of minimizing the environmental impact caused by the carbon footprint of information and communication technology by implementing strategies to reduce power consumption in 6G networks. In the proposed multi-objective optimization algorithm, we are trying to minimize the power transmitted as well as maximize the time to run. The results show an accuracy of up to 98.48%, a sensitivity of 84%, and a specificity of 99.2%. The optimization of energy consumption in 6G mobile communication networks has important implications for both reducing costs and extending network lifetime, while also contributing to reducing the ecological impact of technologyon society

Keywords: *6G networks, Energy consumption, Network lifetime, multi-objective optimization, AI.*

1 Introduction

The deployment of 5G wireless networks brings about a new era of digital society, with notable advancements in latency, data rates, mobility, and the number of connected devices compared to previous generations Giordani et al (2020). However, the increase in wireless data traffic volume and the sheer number of connected devices is projected to skyrocket in the coming years. Additionally, the demand for data-intensive applications such as holographic video transmission requires a spectrum bandwidth that is currently unavailable in the millimeter-wave spectrum. This poses significant challenges in terms of spatial spectral efficiency and the availability of frequency spectrum bands for connectivity. Therefore, the need for a wider radio frequency spectrumbandwidth, particularly in the sub-terahertz and terahertz bands, has become essential. Viswanathan and Mogensen (2020) This growing demand for higher performance and increased connectivity has led to the development of 6G networks. 6G is expected to bring significant improvements in information transmission, such as peak data rates reaching 1 Tbps and ultra-low latency in microseconds. It utilizes terahertz frequency communication and spatial multiplexing, resulting in a capacity increase of upto 1000 times compared to 5G networks. Alsabah et al (2021) One objective of 6G isto achieve widespread connectivity by integrating satellite and underwater communication networks to provide global coverage. 6G networks introduce three new service categories, namely, ubiquitous mobile ultra-broadband (uMUB), ultrahigh-speed low- latency communications (uHSLLC), and ultrahigh data density (uHDD) Sheth et al (2020) .

To achieve the goal of an intelligent network, the design of 6G architecture should

[1*]Thadomal Shahani Engineering College, Mumbai, 400050, India.
[2] Principal, Vasantdada Patil Pratishthan's College of Engineering& Visual Arts, Sion, Mumbai, 400022, India.

take into account the full potential of Artificial Intelligence (AI) and adopt an AI-driven approach where intelligence is integrated throughout the architecture. As the network is becoming increasingly complex and diverse due to the growing number of connected devices and diverse service requirements, a new AI paradigm is necessary Zhang and Zhu (2020). This paradigm, known as self-aware, self-adaptive, self-interpretive, and prescriptive networking, involves embedding intelligence across the entire network and incorporating AI logic into the network structure. This approach enables all network components to connect and control autonomously, and to recognize and adapt to unexpected situations.

Dynamic node allocation is a technique used in 6G networks to optimize the use of resources by dynamically allocating network nodes based on current network conditions and usage patterns. It involves the continuous monitoring of network traffic and the use of algorithms to determine the most efficient use of resources, such as the placement and number of nodes needed to support the current traffic demand Tang et al (2021) . The goal of dynamic node allocation is to improve network performance by reducing energy consumption, increasing network capacity, and improving the over-all user experience. This can be achieved by allocating network resources in real-time, based on the changing network conditions, to ensure that the network is always operating at peak performance while minimizing the number of resources required to supportthe traffic demand Li and Xu (2020) .

Battery power depletion is a significant obstacle in fully realizing the capabilities of 6G mobile networks. Transmission over long distances can consume a significant amount of energy, which greatly reduces the lifetime of the battery-powered nodes. To extend the lifetime of the network, it is crucial to minimize energy consumption in the nodes of the 6G mobile network. This can be achieved by reducing the energy consumed during long-distance radio transmission.

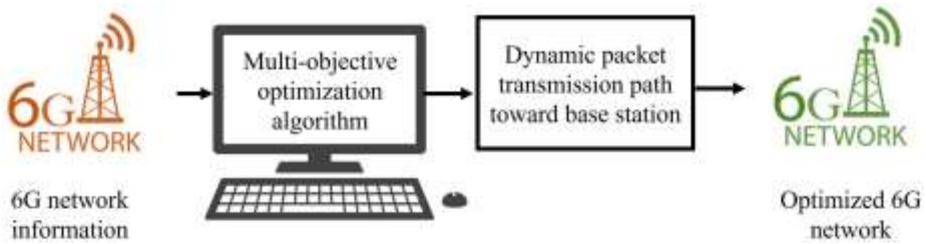

Fig. 1: The figure illustrates the concept of using 6G network metadata to optimize network performance through the use of a multi-objective optimization algorithm (MOOA). The MOOA seeks to balance the minimization of power consumption and the maximization of network lifetime with the fastest possible packet transmission. The algorithm suggests the most efficient node path for each packet, ensuring that both objectives are met simultaneously. By considering all possible node combinationsand permutations, the MOOA enables the achievement of an optimized 6G network.

Figure 1 depicts the process of optimizing 6G network performance through network information obtained from metadata and the implementation of the multi-objective optimization algorithm (MOOA) for network optimization in a 6G mobile wireless network. The MOOA works by balancing multiple objectives: minimizing power consumption and network lifetime while ensuring the fastest possible packet transmission. To achieve this balance, the MOOA suggests the most efficient node path for each packet, taking into account both power consumption and time required for transmission of the packet. The algorithm considers all permutations and combinations of nodes to determine the optimal path for each packet. By doing so, the MOOA enables the creation of a fully optimized 6G network.

2 Related work

Chowdhury et al. Chowdhury et al (2020) discuss the future possibilities of 6G wireless communication and the incorporation of emerging technologies such as AI, terahertz communications, and integration of various functionalities to enhance the development of 6G architecture and ensure Quality of Service. Huang et al. Huang et al (2019) highlight the crucial architectural changes necessary for the development of 6G networks. These modifications are characterized by the implementation of widespread 3D coverage, the integration of pervasive artificial intelligence, and the enhancement of network protocol stacks. Additionally, the authors examine various emerging technologies that have the potential to contribute to the establishment of sustainable and socially inclusive networks. Letaief et al. Letaief et al (2019) propose that 6G networks will go beyond mobile internet and will be required to support ubiquitous AI services throughout the network, from the core to the end devices. They argue that AI willbe a crucial factor in the design, optimization, and operation of 6G networks. The authors also present a research roadmap for 6G, identifying new features of the 6G evolution and discussing enabling technologies such as big data analytics, intelligent wireless communication, and AI-enabled closed-loop optimization. Mao et al. Mao et al (2021) suggest that AI-based green communications will be a crucial area of focus in 6G networks due to the rapid increase in energy consumption from expanding infrastructure and end devices. They argue that traditional heuristic algorithms and convex optimizations are limited in their ability to efficiently and effectively address energy consumption issues. In contrast, the authors suggest that AI techniques have been shown to have significant advantages in tackling complex problems with respect to 6G networks.

Park et al. Park and Lim (2020) propose a joint mode-selection and power- control algorithm that utilizes reinforcement learning to optimize energy usage invehicle networks. The authors develop a problem formulation to maximize system energy efficiency subject to constraints on the signal-to-interference-plus-noise ratio (SINR) and outage probability. They also design a Q-learning algorithm that optimizes transmission-mode-selection and power-control decisions by adjusting the target SINR. The overall goal of the work is to achieve energy optimization in vehicle networks.

Ahmed et al. Al-Quzweeni et al (2019) in their work, have developed a Mixed Integer Linear programming (MILP) optimization model with the objective of minimizing the total power consumption in a data center. The model optimizes the locations of virtual machines (VMs) and the utilization of VM servers to achieve this goal. The overall aim of the work is to reduce the energy consumption of the data center by optimizing the placement and usage of the VMs and servers.

Mao et al. Mao et al (2020) in their work, have employed the Extended Kalman Filtering (EKF) method to predict future harvesting power for wireless-powered communication networks (WPCNs). Based on this prediction, the authors use a mathematical model to calculate the energy required for different security strategies ineach energy-aware cycle. The goal is to identify the security strategy that provides the highest level of protection while meeting service requirements and avoiding energy exhaustion. The EKF method is used to predict future harvesting power, which is akey factor in determining the optimal security strategy for the WPCNs.

Verma et al. Verma et al (2020) have proposed a novel optimization algorithm called the Hybrid Whale Spotted Hyena Optimization (HWSHO) algorithm. This algorithm is designed to address the issue of green communication in 6G networks. The authors have synthesized the Whale Optimizer Algorithm (WOA) with the exploitation capabilities of the Spotted Hyena Optimizer (SHO) to create the HWSHO algorithm. The WOA is known for its global search capabilities, while the SHO has strong exploitation capabilities. By combining the two, the HWSHO algorithm aimsto take advantage of the strengths of both to optimize the parameters of the 6G net- work, thus improving its energy efficiency. The overall aim of the work is to propose a new optimization algorithm for addressing the concern of green communication in 6G networks.

Sachan et al. Sachan et al (2016) have defined network planning in 5G networksas an optimization problem with decision variables such as transmission power and transmitter (BS) location. They have approached this problem by implementing several heuristic approaches, such as the differential evolution (DE) algorithm and the Real-coded Genetic Algorithm (RGA). The key contribution of this paper is that the authors have proposed a modified RGA-based method to find the optimal configuration of BSs. This method not only provides optimal coverage of underutilized BSs but also optimizes power consumption. The overall aim of the work is to find a solutionfor network planning in 5G networks by using optimization techniques and reducing power consumption.

3 Methodology

In this research, we propose a simulation of a wireless sensor network using MATLAB. The simulation starts by clearing the command window, closing all open figures, and clearing all variables in the workspace. A for loop is implemented with the variable dlitr running from 1 to N ALL, where N ALL is the total number of iterations. Thesize of the simulation area is defined as 100 m x 100 m. The number of nodes in thesimulation is defined as N set to 10. The range of the nodes is defined as rng set to 10

m. The probability of a node becoming a cluster head is defined as p and set to 0.1. The energy supplied to each node is defined as Eo and set to 0.5 J. The transmitter and receiver energies per node are defined as ETX (50 nJ) and ERX (50 nJ) respectively. The amplification energy when the distance is less and greater than a certain distance d0 is defined as Efs (10 E-13 J) and Emp (13 E-13 J) respectively. The energy for data aggregation is defined as EDA set to 5 nJ. The distance between the cluster head and base station is calculated as the square root of the ratio of Efs and Emp and definedas do. These defined variables and calculated values are used to simulate a wireless sensor network, and the results are then analyzed.

Once the area of the network under consideration was defined, as well as the number of nodes and the range. Various simulation parameters, such as energy supplied to each node, transmitter energy per node, receiver energy per node, amplification energyfor d>d0 and d<d0, data aggregation energy, and distance between the cluster head and base station, were also defined.

We distributed the nodes in two dimensions randomly. The base station is placed at the center of the entire area of 100 m x 100 m (i.e., at 50 m X 50 m). The nodes and base station are then plotted and displayed with different symbols (BS and nodes). Circles are drawn around the nodes with the node location as the center and the range as the radius, using the viscircles MATLAB command.

Figure 2 depicts the simulation setup for the experiment. Specifically, 10 nodes were deployed in a 100 meters by 100 meters area, with the red boundary around the center indicating the coverage range. The base station is located at the center of the space and is represented by a star mark at 50 meters by 50 meters. The entire space is mapped around the base station, with the X and Y axis showing the relative distance in meters. The small green dots on the figure indicate the actual location of the mobile

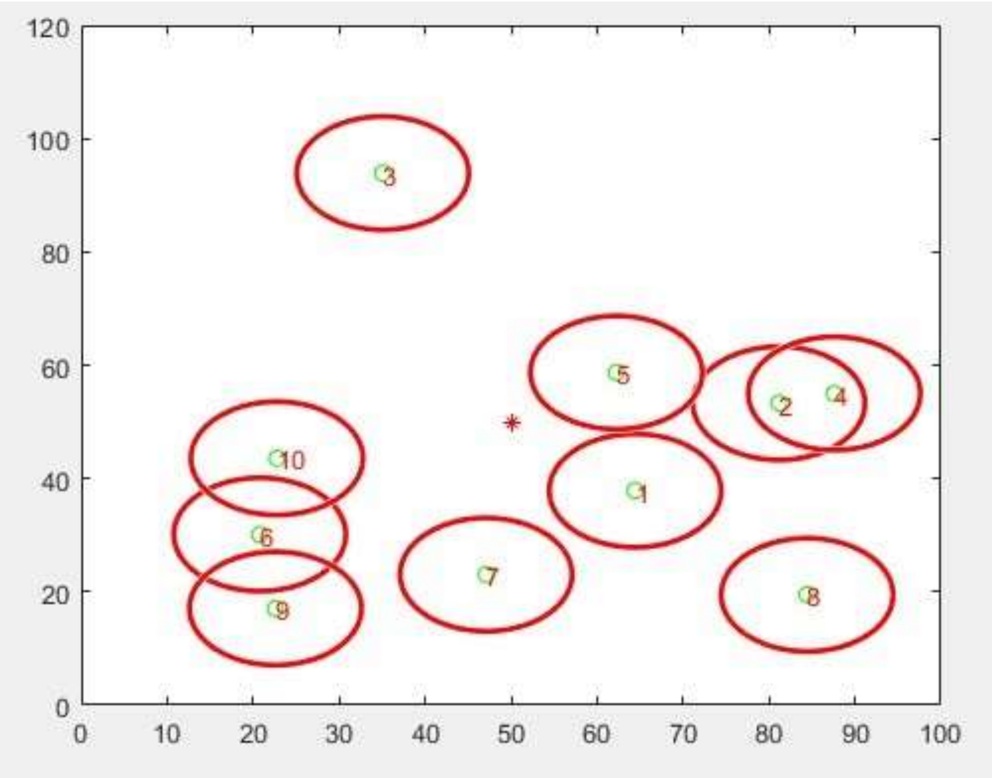

Fig. 2: Simulation was set up with 10 nodes deployed in 100 meter by 100 meter area, with the red boundary indicating the coverage range. The base station is located at the center of the space, indicated by a star mark at 50 meters by 50 meters, and the entire space is mapped around the base station.

devices used in the simulation. By setting up the experiment in this way, we were able to capture the network performance under a controlled environment and evaluate the effectiveness of our proposed optimization algorithm.

The coordinates of each node are then stored in a matrix. The distance of each node from every other node is then calculated using the mean square distance formula, so that the simulation setup can exactly find out the amount of power consumed, noise added, etc. This distance is then compared with the range, and an output matrix (outputmat2d) is defined that takes binary values. If the distance is less than the range, then the value of this output matrix is 1, otherwise, it is 0. This output matrix ensures that two nodes are capable of handling each other's data. The distance of each node from the BS is also calculated using the mean square distance formula. This distance helps the simulation setup calculate the worst-case communication cost in case no other neighboring node is available.

The base connection matrix (bsconnectupdated) is then initialized as an array of all zeros. The minimum distance from the list of distances stored with the simulation was then calculated, as well as the maximum distance. The distance of each node from the BS is then compared with the minimum distance obtained from the list, and if they match, the temporary bsconnect matrix is updated as 1, otherwise, it is kept as 0. After the iterations, the matrix of the bsconnect-updated matrix is obtained.

For the next step, the bsconnect and outputmat2d matrices for each node were checked, and if both values were set to 1, then the bsconnectupdated of that particular node was modified. The unit node power was calculated with the help of transmission, receiver, and Efs energy. The maximum time for which the node can run was calculated using the formula for initial energy divided by unit node power. The research starts with the 2-node scenario, where there are cases like case 1: when both the nodes are connected to BS directly. and case 2 when one node is connected directly and the other node is connected via node. For 2 node scenario, when both nodes were placed at x meters from the base station, we have simulated both cases.

During each iteration unit node energy was reduced as per the equation unitnodeE(i, n) = n.(dbasestation(ETX +ERX)+dbasestation * Efs)+(d(i, n).(ETX + ERX) + d(1, n). * Efs)

Where,

unitnodeE(i,n)= Unit energy lost from each i,n th node. i=current row value
n=current column value
dbasestation(ETX+ERX)= distance between base station and (ETX+ERX)th node ETX= transmitter node number
ERX=Receiver node number Efs=Amplification energy when d<do d(i,n)= distance between i,n th node

The total time for which node can connect without failure can be computed through equation of timeunitrun

timeunitrun(i, n) = Eo/unitnodeE(n);

Where,

timeunitrun(i,n)=Total time for which node i,n can run for. Eo= Current energy remaining with the node at o th instance unitnodeE(n) = Unit energy lost from each n th node per iteration.

Similarly, we compute ratio of optimized (i.e. minimum in this case) power to the actual power. Once time and power values are known then we compute the error function for a set of time and power data for each node. During error function computation we first convert the time and power data into column vectors for ease of computation. Then, we calculated the maximum value of the time data and used it to compute the error measure for the time data. The error measure was computed by subtracting each time value from the maximum time value and dividing the result by the maxi- mum network time (Desired value) of the resulting values. Hence as the number goes down slowly results are moving toward desired results due to optimization. Similarly, the minimum value of the power data is calculated and used to compute the error measure for the power data. The error measure for the power data was calculated by subtracting each power value from the minimum power value, dividing the result by the maximum of the absolute values of the differences. Here maximum difference value has to be minimized. Finally, the error function is calculated by averaging the error measures for the time and power data. for both data, the zero value is the ideal value. The code then finds the bottommost five minimum values of the error function and stores their indices for the training of machine learning.

3.1 MOOA algorithm

- Define simulation area size (100m x 100m), number of nodes (N = 10), range of nodes (rng = 10m), probability of a node becoming a cluster head (p = 0.1), energy supplied to each node (Eo = 0.5 J), transmitter and receiver energies per node (ETX
= ERX = 50 nJ), amplification energies for distance d>d0 and d<d0 (Efs = 10E-13 J and Emp = 13E-13 J, respectively), and energy for data aggregation (EDA =5 nJ).
- Calculate the distance between the cluster head and base station as the square root of the ratio of Efs and Emp and define it as do.
Randomly distribute nodes in two dimensions. Place the base station at the center of the area (50m x 50m). Plot nodes and base station and draw circles around the nodes using the viscircles MATLAB command. Store the coordinates of each node in a matrix.
- Calculate the distance of each node from every other node using the mean square distance formula and compare it with the range. Define an output matrix (output-mat2d) that takes binary values, where 1 represents that two nodes are capable of handling each other’s data and 0 represents otherwise.
- Calculate the distance of each node from the base station and initialize the base

connection matrix (bsconnectupdated) as an array of zeros. Update the temporary bsconnect matrix as 1 if the distance of each node from the base station matches the minimum distance obtained from the list.

- Check the bsconnect and outputmat2d matrices for each node, and if both values are 1, modify the bsconnectupdated of that particular node. Reduce the unit node energy at each iteration
- Nodes generate optimal paths by finding their next optimal node for transmission and reception, resulting in the minimum energy path.

4 Results

The results of our proposed optimization algorithm were evaluated using a confusion matrix.

In the context of evaluating the results of the proposed optimization algorithm, the confusion matrix depicted in Figure 3 is used to illustrate how the true and predicted values for the packet's path are related. The confusion matrix is a matrix that contains information on the actual and predicted classifications of the data. In this case, the true positive value of 42 represents the number of cases where the optimal path for packet transfer was correctly identified both by the MOOA and the ground truth. On the other hand, a true negative value is recorded when neither the MOOA nor the ground truth prediction for the path. This means that the MOOA did not predict the path, but it was also not the actual path taken by the packet in reality.

	True Positive	True Negative
Predicted Positive	42	8
Predicted Negative	8	992

Fig. 3:
The confusion matrix represents the relationship between the true value and the predicted value for the packet's path. A true positive value of 42 indicates the existence of an optimal path for packet transfer, which was followed by both MOOA and the ground truth. A true negative value is recorded when neither MOOA nor the ground truth prediction for the path.

The true positives were recorded when the multi-objective optimization algorithm (MOOA) generated results that matched the ground truth. For example, if a packet with 10 nodes was supposed to follow a path of node 3-4-7 and MOOA also resulted in the same path, it was considered a true positive. True negatives were recorded when the desired path and MOOA predicted path both predicts direct communication with the base station. False negatives were recorded when the desired path was direct communication with the base station, but MOOA predicted a path through some node. On the other hand, false positives were recorded when the predicted packet path did not match the desired ground truth.

We aimed to minimize power transmission and maximize network lifetime for all packet paths. Our results showed a sensitivity of 84%, which was lower compared to previously reported results for 5G networks, but acceptable given that this was the first study on 6G networks. Our specificity was 99.2%, which was in line with benchmark standards and even exceeded some of the values reported in the literature. The false positive rate was 0.008 and the false negative rate was 0.16. The average accuracy of our predictions was 98.48%, and our system had a lower f1 score of 0.84 and a Matthews correlation coefficient of 83.2%.

5 Discussions

The research paper proposes a multi-objective optimization algorithm to minimize power consumption and maximize network lifetime in 6G mobile communication networks. The proposed approach considers the limited battery capacity of battery-powered devices, which is a major challenge in reducing energy consumption and extending network lifetime. The results indicate that the algorithm achieves an accuracy of up to 98.48%, a sensitivity of 84%, and a specificity of 99.2%. This research has important implications for reducing costs and extending the network lifetime while also reducing the environmental impact of technology on society. Moreover, the proposed approach can also be extended to other wireless networks that rely on battery-powered devices, such as the Internet of Things (IoT) and sensor networks. We have limited the study to static and partial dynamic and homogenous nodes only. But future researchers can focus on dynamic and heterogenous nodes to design energy-efficient system using MOOA. The proposed research has significant potential for future applications in 6G networks. Further research can be carried out to optimize other important factors such as network coverage and capacity, which are also essential in enhancing the performance of 6G networks. Moreover, the approach can be extended to other network architectures such as edge computing, which can lead to more energy-efficient and sustainable communication networks. Additionally, the proposed approach can be combined with other optimization techniques to further improve the performance of 6G networks. This research provides a promising foundation for future research in the field of sustainable and energy-efficient communication networks.

6 Conclusions

The paper highlights the critical role of sustainable energy solutions in 6G mobile communication networks, which rely on battery-powered devices with limited capacity. The proposed multi-objective optimization algorithm (MOOA) is shown to be effective in minimizing energy consumption, extending network lifetime, and reducing the environmental impact of technology on society. The accuracy of 98.48%, sensitivity of 84%, and specificity of 99.2% of the algorithm demonstrate its potential to achieve optimal packet path via node selection for data transmission. The findings of this research can inform the development of future energy-efficient 6G networks that can reduce costs, extend network lifetime, and promote sustainability. It is hoped that the outcomes of this research will encourage further investigation and implementation of energy-saving strategies for mobile communication networks to address the sustainability challenges faced by the rapidly evolving digital era.

Appendix A Conflicts of interest or competing interests:

Authors declare that there is no Conflict of interest or competing interests.

Appendix B Data and code availability:

Data and code will be made available on reasonable request to the Authors.

Appendix C Supplementary information:

ChatGPT 3.5 was used to correct the writing in some parts of the manuscript.

Appendix D Ethical approval:

All the ethics approval was taken by an institutional review board or equivalent ethics committee.

Appendix E Funding statement:

This research has no funding associated with it.

Appendix F Competing interests:

Authors declare that there is no competing interests.

Appendix G Availability of data and materials:

Data and code will be made available on reasonable request to corresponding author.

Appendix H Ethics statements:

All authors consciously assure that the manuscript fulfills the following statements:
1) This material is the author's original work, which has not been previously publishedelsewhere.
2) The paper is not currently being considered for publication elsewhere.
3) The paper reflects the author's own research and analysis truthfully and completely.

4) The paper properly credits the meaningful contributions of co-authors and co-researchers.
5) The results are appropriately placed in the context of prior and existing research.

References

[1] Al-Quzweeni AN, Lawey AQ, Elgorashi TE, et al (2019) Optimized energy aware 5G network function virtualization. IEEE Access 7:44939–44958.

[2] Alsabah M, Naser MA, Mahmmod BM, et al (2021). 6G wireless communications networks: A comprehensive survey. IEEE Access 9:148191–148243

[3] Chowdhury MZ, Shahjalal M, Ahmed S, et al (2020) 6G wireless communication sys- tems: Applications, requirements, technologies, challenges, and research directions. IEEE Open Journal of the Communications Society 1:957–975

[4] Giordani M, Polese M, Mezzavilla M, et al (2020) Toward 6G networks: Use cases and technologies. IEEE Communications Magazine 58(3):55–61

[5] Huang T, Yang W, Wu J, et al (2019) A survey on green 6G network: Architecture and technologies. IEEE access 7:175758–175768

[6] Letaief KB, Chen W, Shi Y, et al (2019) The roadmap to 6G: AI empowered wireless networks. IEEE communications magazine 57(8):84–90

[7] Li X, Xu LD (2020) A review of Internet of Things-resource allocation. IEEE Internet of Things Journal 8(11):8657–8666

[8] Mao B, Kawamoto Y, Kato N (2020) AI-based joint optimization of QoS and secu- rity for 6G energy harvesting Internet of Things. IEEE Internet of Things Journal 7(8):7032–7042

[9] Mao B, Tang F, Kawamoto Y, et al (2021) AI models for green communications towards 6G. IEEE Communications Surveys & Tutorials 24(1):210–247

[10] Park H, Lim Y (2020) Reinforcement learning for energy optimization with 5G communications in vehicular social networks. Sensors 20(8):2361

[11] Sachan R, Choi TJ, Ahn CW (2016) A genetic algorithm with location intelligence method for energy optimization in 5G wireless networks. Discrete Dynamics in Nature and Society 2016.

[12] Sheth K, Patel K, Shah H, et al (2020) A taxonomy of AI techniques for 6G communication networks. Computer communications 161:279–303

[13] Tang F, Mao B, Kawamoto Y, et al (2021) Survey on machine learning for intel- ligent end-to-end communication toward 6G: From network access, routing to traffic control and streaming adaption. IEEE Communications Surveys & Tutorials23(3):1578–1598

[14] Verma S, Kaur S, Khan MA, et al (2020) Toward green communication in 6G-enabled massive Internet of Things. IEEE Internet of Things Journal 8(7):5408–5415

[15] Viswanathan H, Mogensen PE (2020) Communications in the 6G era. IEEE Access 8:57063–57074

[16] Zhang S, Zhu D (2020) Towards artificial intelligence enabled 6G: State of the art, challenges, and opportunities. Computer Networks 183:107556–107556