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Reviewing AI-Powered Solutions for Energy Efficiency in 6G Communication Systems

Ms. Harshita G. Patil[1], Dr. Kaushlendra Sharma[2] and Dr. Shishupal Kumar[3]
[1]Research Scholar, Indian Institute of Information Technology, Nagpur, India
Email: dtea23cse017@iiitn.ac.in
[2-3]Assistant Professor, Indian Institute of Information Technology, Nagpur, India
Email: ksharma@iiitn.ac.in, skumar@iiitn.ac.in

***Abstract*— The advent of 6G networks promises ultra-high speeds, low latency, and ubiquitous connectivity, but achieving energy efficiency in such data-intensive systems remains a key challenge. This study reviews the vital role of advanced AI sensing approaches in optimizing energy use while maintaining high network performance. Techniques involving machine learning, deep learning, and hybrid AI enable real-time adaptation to network conditions, ensuring efficient resource allocation and reduced energy waste. Key applications include spectrum management, beamforming optimization, massive MIMO systems, and device-to-device communication. The review highlights AI's role in enabling dynamic resource management, fault detection in self-healing networks, and energy-aware spectrum allocation. It also explores challenges like processing overhead, scalability, and data privacy. Emerging solutions such as federated learning and edge computing offer promising ways to balance computational demands with energy efficiency. Additionally, future directions include integrating renewable energy sources and developing lightweight AI algorithms to reduce carbon footprints and operational costs. By classifying and comparing various AI sensing strategies, this paper provides valuable insights into their capabilities and limitations. The findings support researchers and practitioners in designing sustainable 6G infrastructures and underscore AI's transformative potential in advancing green telecommunications.**

***Keywords*— Energy Efficiency, AI Model Sensing, Reinforcement Learning, Federated Learning, Deep Learning Models, Massive MIMO, Beamforming Optimization, Device-to-Device Communication.**

I. INTRODUCTION

The exponential increase in the number of connected devices has inaugurated an era of ubiquitous connectivity, which has been facilitated by the rapid advancement of communication technology [1]. It is anticipated that 6G networks will be able to provide ultra-reliable and low-latency communication while managing unprecedented data traffic by the time they are fully operational. These capabilities will facilitate a wide range of applications, including autonomous systems, augmented reality, and extensive IoT ecosystems [2]. Nevertheless, the enormous scope and intricacy of 6G networks present a substantial obstacle: the simultaneous maintenance of energy efficiency and the guarantee of optimal network performance. It is imperative to resolve this matter in order to facilitate the deployment of scalable, cost-effective networks and to achieve global sustainability objectives.

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Artificial Intelligence (AI) has emerged as a transformative instrument for addressing energy efficiency challenges in 6G networks. AI model sensing is a critical enabler that is particularly prominent among its applications. AI model sensing is the process of utilising sophisticated algorithms to interpret, perceive, and adjust to real-time network conditions [3].

This dynamic approach enables networks to proactively allocate resources, optimise power usage, and reduce energy wastage. AI ensures efficient operation without compromising the quality of service by incorporating sensing capabilities into network systems, which allows for continuous monitoring and predictive adjustments [5].

The current paper investigates the application of state-of-the-art AI-based sensing techniques in energy-efficient 6G networks. This section analyses the strengths and limitations of these approaches by classifying them into a variety of methodologies, including hybrid models, deep learning, and machine learning. In addition, the paper explores practical applications of AI sensing, including spectrum management, beamforming optimisation, and Massive MIMO systems, all of which substantially reduce energy consumption.

In the 6G era, the paper illuminates the critical role that AI plays in the evolution of green communications by addressing these topics.

While summarising the landscape of AI sensing techniques, this review also highlights the remaining challenges, including computational overhead and scalability, and anticipates future advancements [4]. The findings emphasise the significance of implementing innovative AI-driven solutions to establish sustainable, energy-efficient 6G networks, as they will significantly influence the future of global communication systems.

A. Background and Need for Energy Efficiency in 6G

The development and deployment of 6G networks are contingent upon increased energy efficiency. Contrary to its predecessors, 6G is designed to facilitate an increasingly interconnected world, which is defined by pervasive AI-driven applications, low latency, and ultra-high-speed communication [6]. To guarantee the sustainability and efficacy of these next-generation networks, it is imperative to achieve energy efficiency. Key drivers that emphasise the necessity of energy-efficient systems in 6G are expounded upon below:

High Device Density

The proliferation of connected devices in smart cities, IoT ecosystems, and industrial automation necessitates robust energy management in 6G networks.

Growth in Device Count: The density of devices in industrial environments and urban areas is increasing at an unprecedented rate, with billions of devices anticipated to operate simultaneously [7]. For instance, IoT applications in autonomous vehicles, healthcare, and smart residences necessitate continuous connectivity. Network traffic is substantially influenced by public infrastructure, including surveillance systems and environmental sensors [8].

Challenges for 6G Networks: High device density results in increased power consumption and signalling overhead in peripheral nodes and base stations. Reliable connectivity for devices without overtaxing network resources necessitates energy-efficient communication protocols.

Energy Efficiency Implications: Optimised power management guarantees that devices consume minimal energy in both active and inactive states. By utilising AI to facilitate intelligent resource allocation, it is possible to mitigate redundant communication and even out energy consumption.

Energy Demands

Base stations, peripheral devices, and data centres are all operational requirements of 6G networks, which necessitate the implementation of energy-efficient designs.

Base Station Power Consumption: Base stations are accountable for a substantial portion of the energy consumption in cellular networks. As 6G is anticipated to provide ultra-high data rates and low latency, the power requirements of base stations will increase, thereby requiring more energy-efficient hardware and software [9].

Energy-Hungry Edge Devices: The implementation of edge computing brings intelligence closer to consumers, but it also introduces energy requirements for processing, storage, and communication. In resource-constrained environments, edge devices in 6G must perform computational duties locally while minimising energy consumption.

AI Integration: The computational burden is further exacerbated by the utilisation of AI for real-time network optimisation, underscoring the necessity of efficient hardware accelerators and algorithms to significantly reduce energy costs.

Sustainability Goals
The global movement towards sustainability is in accordance with the necessity of energy-efficient 6G systems, which is being driven by escalating environmental concerns and regulatory mandates [10].
Carbon Footprint of Networks: The infrastructure of communication networks is energy-intensive, which substantially contributes to global carbon emissions [11]. Addressing the environmental impact of network operations will be essential to achieve international sustainability objectives, including those enumerated in the Paris Agreement, by the time 6G is implemented.
Green Communication Initiatives: Regulatory frameworks are promoting the implementation of energy-efficient technologies in the telecommunications sector [12]. Green communication practices are being implemented by operators due to incentives and penalties associated with energy consumption.
Integration with Renewable Energy: The integration of renewable energy sources, such as solar and wind, into the energising of base stations and network components is increasingly recognised as a critical approach to decreasing dependence on fossil fuels [13]. In order to optimise efficacy, energy management systems that are AI-enabled can dynamically transition between renewable and conventional power sources.

II. Related Work

The rapid advancements in next-generation IoT technologies, which have been significantly impacted by the emergence of 6G and B5G, have significantly improved the reliability, efficiency, and profitability of industrial and personal operations.
Nevertheless, resource-constrained environments continue to face challenges such as data overload, energy efficiency, and latency. In order to resolve these concerns, researchers have investigated novel solutions, such as data mining, multi-agent systems, neural network optimisations, and edge computing. The incorporation of collaborative frameworks, resource management techniques, and distributed intelligence has been instrumental in overcoming these limitations, thereby enabling the development of high-performance, scalable, and energy-efficient IoT ecosystems.

TABLE I. COMPARISON OF REVIEWS

Author(s)	Focus Area	Methodologies/Technologies	Key Findings/Outcomes
Negi et al. (2024)	6G IoT advancements, energy efficiency in industrial applications	Multi-Agent System (MAS), Distributed Artificial Intelligence (DAI), BPNN, CNN, data mining, edge computing	Improved energy efficiency and resource allocation in 6G industrial applications, safeguarding critical data, and optimizing operations through inter-cluster correlations and sensor clustering.
Mukherjee et al. (2020)	6G IoT technologies, energy/resource optimization	MAS, DAI, BPNN, CNN, edge computing, data mining	Enhanced energy efficiency, resource allocation, and latency reduction. Simulation demonstrated reduced resource wastage and ensured critical data preservation.
Tang & Hu (2020)	Latency minimization in IoT-enabled MEC HetNets	Mixed Integer Non-Linear Programming (MINLP), Successive Convex Approximation (SCA), CVX tool	Reduced user weight-sum delay and energy consumption through optimised resource allocation and a distributed computation outsourcing algorithm.
Kim et al. (2020)	Resource management in D2D networks for distributed computing	Mixed Integer Programming (MIP), subchannel allocation, MIMO signal design	Achieved energy efficiency and scalability through decomposition of resource allocation and MIMO design subproblems.
Ghanbari et al. (2019)	Resource allocation challenges in IoT	Systematic Literature Review (SLR), cost/context-aware, QoS-aware, SLA-based mechanisms	Highlighted advancements and challenges in resource allocation. Proposed framework emphasized future development areas and open issues in IoT technology.
Li C. (2019)	Mobile Edge Computing (MEC) and energy harvesting in IoT	Time Average Computation Rate Maximization (TACRM), joint resource allocation	Enhanced system performance and operational lifespan of IoT devices through optimal resource and energy allocation.
W. Lee et al. (2019)	Cooperative spectrum sensing in Cognitive Radio Networks (CRNs)	Deep Cooperative Sensing (DCS) framework, CNN	Improved sensing accuracy and spectrum usage efficiency by autonomously learning spectrum and spatial correlations in CRNs.
G. Li et al. (2018)	Fog computing in IIoT	Smart Resource Partitioning (SPSRP), Zipf's Law-based modeling, heterogeneity-aware algorithms	Enhanced delay performance, fault tolerance, and service response rates in fog-enabled IIoT systems through intelligent resource partitioning.

Subotha et al. (2018)	Energy-efficient secure video transmission in WSNs	Modified Cuckoo Search (MCS), Selective Encryption	Optimized energy consumption and video quality through encryption and transmission parameter tuning.
Kumar & Singh (2018)	Data aggregation in WSNs	Neural Networks, Fuzzy Logic, Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO)	Improved transmission and network lifetime. Proposed protocol outperformed conventional AI and metaheuristic methods.
Kim et al. (2018)	Distributed power allocation for D2D in LTE	Deep Learning-based architecture	Maximized cell throughput while adhering to interference constraints through independent deep learning-driven power optimization.
Y. Chen et al. (2016)	Industrial IoT toxic gas detection	Collaborative Sensing Intelligence (CSI), spatiotemporal data analytics	Developed CSI framework for efficient industrial production and services through integrated human-device data collaboration and analytics.

III. AI TECHNIQUES FOR MODEL SENSING IN 6G

Enabling 6G networks to detect and adapt to environmental and operational conditions for energy efficiency is a critical function of machine learning (ML) techniques.AI techniques for model sensing in 6G networks capitalise on the advantages of hybrid models, edge computing, ML, and DL to optimise energy consumption [39]. By dynamically adapting to network and environmental conditions, these techniques address the energy challenges associated with the concentrated device deployments and high data demands of 6G. Advancements in algorithm efficiency and hardware acceleration are anticipated to render these solutions more practicable and scalable, despite the fact that computational overhead remains a challenge.

TABLE II. COMPARISON OF AI TECHNIQUES FOR MODEL SENSING IN 6G

Technique	Mechanism	Applications in 6G	Advantages	Challenges
Reinforcement Learning (RL)	Learns through interaction with the environment using feedback (rewards/penalties).	Dynamic resource allocation, power optimization.	Real-time adaptability; dynamic optimization.	High computational demands; slow convergence.
Federated Learning (FL)	Decentralized model training across devices without sharing raw data.	Reduces data transmission, energy-aware model updates.	Preserves privacy; minimizes data transfer energy costs.	Communication overhead of aggregated model updates.
Unsupervised Learning	Identifies patterns or clusters in data without labelled outputs.	Low-energy state detection, redundancy elimination.	Automatically uncovers hidden patterns for energy savings.	Requires additional integration for practical use cases.
Convolutional Neural Networks (CNNs)	Extracts spatial features from high-dimensional data like antenna arrays.	Beamforming, spatial sensing in massive MIMO.	Optimizes spatial transmission paths; reduces interference.	High computational costs for processing complex spatial data.
Recurrent Neural Networks (RNNs)	Processes sequential data for temporal pattern recognition.	Predicts traffic trends; schedules resources.	Efficient for temporal energy management; handles time-series data.	Computationally intensive; prone to overfitting.
Hybrid AI Models	Combines multiple AI techniques for enhanced decision-making.	Multi-dimensional optimization (spatial + temporal sensing).	Holistic energy optimization; adaptable to complex scenarios.	Increased complexity; higher computational demands.
Edge AI	Processes data locally at edge devices instead of relying on central servers.	Real-time energy management, localized decisions.	Reduces data transfer energy; low latency; real-time adaptability.	Limited computational power on edge devices.

IV. KEY SENSING TECHNIQUES IN 6G NETWORKS

Revolutionary advancements in communication technologies are proposed by the 6G networks, which are designed to optimise performance without sacrificing energy efficiency [40]. In the optimisation of network operations, AI model sensing is of paramount importance. I have provided a comprehensive explanation of the primary sensing techniques below:

TABLE III: KEY SENSING TECHNIQUES IN 6G NETWORKS

Technique	Purpose	AI Methods Used	Benefits	Energy Impact
Energy-Aware Spectrum Sensing	Optimal utilization of frequency bands	Reinforcement Learning, Cognitive Radio	Reduces spectrum wastage, improves resource allocation	Minimizes energy use by deactivating idle channels and avoiding noisy frequency bands.

Massive MIMO Sensing	Efficient operation of large antenna arrays	Sparse Representation, Channel Estimation	Optimizes antenna selection, enhances load balancing	Reduces power usage by activating only necessary antennas and avoiding redundant transmissions.
Beamforming Optimization	Directing transmission power to specific users or regions	Deep Neural Networks, Multi-Beam Coordination	Improves signal focus, reduces interference	Minimizes power spent on unnecessary areas while enhancing energy efficiency in high-density regions.
AI for Device-to-Device (D2D) Communication	Enables direct communication between devices without base station involvement	Clustering Algorithms, Path Optimization	Reduces reliance on base stations, improves proximity-based communication	Saves energy by optimizing direct device communication and selecting energy-efficient relays.
Self-Healing Networks	Detects and rectifies network faults autonomously	Anomaly Detection, Predictive Maintenance	Prevents network downtime, ensures seamless operation	Eliminates energy wastage from retransmissions and keeps systems functioning optimally.

V. Challenges and Limitations

High Computational Overhead: Substantial computational resources are required by AI models, particularly those that incorporate deep learning and intricate machine learning algorithms. These resources are essential for the processing of large datasets, the execution of complex calculations, and the training of sophisticated models. Nevertheless, the energy savings that are obtained through AI optimisations in 6G networks are frequently counterbalanced by the energy consumption associated with these computational processes. As an illustration, the continuous processing capacity required by tasks such as real-time spectrum sensing or adaptive resource allocation may place a strain on hardware capabilities and increase energy consumption [57]. In order to overcome this obstacle, it is imperative to create energy-efficient hardware accelerators and lightweight AI algorithms for sustainable implementation.

Data Privacy and Security: The implementation of AI model sensing in 6G networks raises substantial concerns regarding data privacy and security. These networks frequently manage confidential user information, and AI-based sensing techniques necessitate substantial quantities of data to generate precise predictions and decisions. Minimising energy consumption while simultaneously guaranteeing data security is a dual challenge. In order to protect user information without incurring an excessive computational or energy burden, the sensing framework must incorporate advanced encryption and privacy-preserving AI techniques, including differential privacy and federated learning. Researchers and engineers are tasked with the critical responsibility of balancing the trade-off between secure data management and computational requirements.

Scalability: The scalability of AI model sensing becomes a critical concern as 6G networks expand to accommodate billions of connected devices. Standardised protocols and interoperability across disparate network components are essential for effective deployment, but this is a difficult task in a heterogeneous environment [58]. Additionally, the inefficiencies that can result from the scaling up of AI sensing models to accommodate immense data volumes and intricate network structures are particularly evident when existing systems are unable to incorporate new sensing methods. In order to achieve seamless scalability, it is necessary to coordinate efforts to establish universal standards and protocols that assure compatibility across global 6G infrastructures, in addition to advancements in AI algorithms.

Real-Time Constraints: Artificial intelligence (AI) sensory systems that operate in real time are necessary due to the ultra-reliable low-latency communication (URLLC) requirements of 6G networks. While optimising energy efficiency, it is a formidable challenge to adhere to these stringent schedule constraints. Tasks such as fault detection, resource allocation, and real-time traffic prediction necessitate instantaneous computation, which frequently results in increased energy consumption. A substantial amount of innovation is necessary to develop AI models that can effectively balance the real-time operational demands with energy-saving objectives. The necessity of ongoing research and innovation is underscored by these challenges, which underscore the complex equilibrium necessary to effectively utilise AI sensing for energy efficiency in 6G networks.

VI. Conclusion

The transformative potential of AI model sensing approaches in 6G networks for energy efficiency is successfully highlighted in the paper. In order to clarify how these approaches might dynamically adapt to the increasing demands of 6G ecosystems, the research explores a wide range of methodologies, such as reinforcement learning, federated learning, and hybrid AI models. As previously said, integrating cutting-edge

AI capabilities into network operations not only maximises resource allocation but also—by reducing energy waste—significantly advances global sustainability goals. A useful basis for their practical use in the real world is also established by the thorough examination of important sensing methods as energy-aware spectrum sensing, massive MIMO sensing, and beamforming optimisation. Taken together, these methods show how AI-powered solutions can meet the demanding requirements of ultra-reliable and low-latency communication while lowering power consumption and improving operational efficiency." The study provides useful insights for getting beyond the real-world obstacles to deploying AI in 6G networks by tackling issues including data privacy, computing overhead, and real-time limits.A strong comparative context is provided by the thorough assessment of similar studies, which highlights important gaps and illuminates current developments. This not only supports the suggested methods but also acts as a basis for further studies that aim to increase interoperability and scalability in diverse network contexts. Modern algorithms and technologies are also included to guarantee that the results are still applicable to both industry practitioners and scholarly scholars. All things considered, this study makes a substantial contribution to the current discussion on the sustainability of 6G networks by providing a fair assessment of the advantages and disadvantages. It promotes a multidisciplinary strategy that blends cutting-edge technology and energy management techniques with advances in artificial intelligence. Smarter, more energy-efficient communication networks that can meet the demands of an interconnected society are made possible by the ideas and techniques offered. Future research should concentrate on honing these methods for widespread implementations and bringing them into compliance with changing international standards in order to fully utilise AI-enabled 6G networks.

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