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TOPICAL REVIEW

Designing Future Wireless Networks (FWN)s With Net Zero (NZ) and Zero Touch (ZT) Perspective

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ABSTRACT Recent research in Future Wireless Networks (FWN)s have primarily focused on improving spectral and energy efficiency, emphasizing less on reducing power consumption. Studies on current Fifth-Generation (5G) system deployment have shown that they consume more power than their predecessors, thus highlighting the need for significant efforts to minimize their carbon footprint. This work specifically focuses on the power consumption considerations, starting from the transceiver design and extending to an entire network design that can accomplish future Net Zero (NZ) targets. It is envisioned that smart grid-controlled renewable-powered systems, combined with artificial intelligence (AI) algorithms and Zero Touch (ZT) solutions, will play a central role to achieve Net Zero - Zero Touch Future Wireless Networks (NZ-ZT-FWNs). This work thoroughly investigates the recent research efforts, limitations of existing approaches and identifies key research areas for realizing NZ-ZT-FWNs.

INDEX TERMS Wireless networks, massive MIMO, net zero, zero touch, energy efficient, power efficient, renewable energy, mmWave communication, THz communication.

I. INTRODUCTION

Global warming has transitioned from being a mere topic of discussion to a harsh reality with dire consequences expected in the coming years [1]. Given the severity of this issue, timely efforts from all industries are required [2]. The Information Communication Technology (ICT) industry currently accounts for approximately 2% of global emissions, which is projected to rise to an alarming 23% by 2030 [3]. Therefore, it is crucial for the ICT industry to take significant measures to align with global Net Zero (NZ) targets. However, current research on Fifth-Generation (5G) is predominantly focused on improving Spectral Efficiency (SE) and Energy Efficiency (EE) [4], [5], [6]. While 5G has achieved higher SE and EE compared to its predecessors, it has also resulted in increased power consumption and higher carbon emissions [7]. It is noteworthy that further expansion of antennas, bandwidth, and Base Stations (BS)s will lead to an increase in the overall power consumption of the wireless network, with projections of up to 20% of the total power consumption of the ICT industry [13]. As a result, it is imperative to proactively incorporate measures, in the design of Future Wireless Networks (FWN)s to minimize the carbon footprint associated with future ICT systems.

FWNs are expected to have even more stringent data rate requirements to enable anticipated technologies such as holographic communication and tele-immersive video conferencing [8]. To achieve these requirements and reduce the carbon footprint, it is envisioned that Cell-Free Networks (CFNs) [9] powered by renewable energy sources and smart grids, utilizing MicroWave (μW), millimeter Wave (mmW) [5], [6], Tera-Hertz (THz) band [10], as well as massive Multiple Input Multiple Output (mMIMO) systems [11], edge computing, and extreme densification will be an

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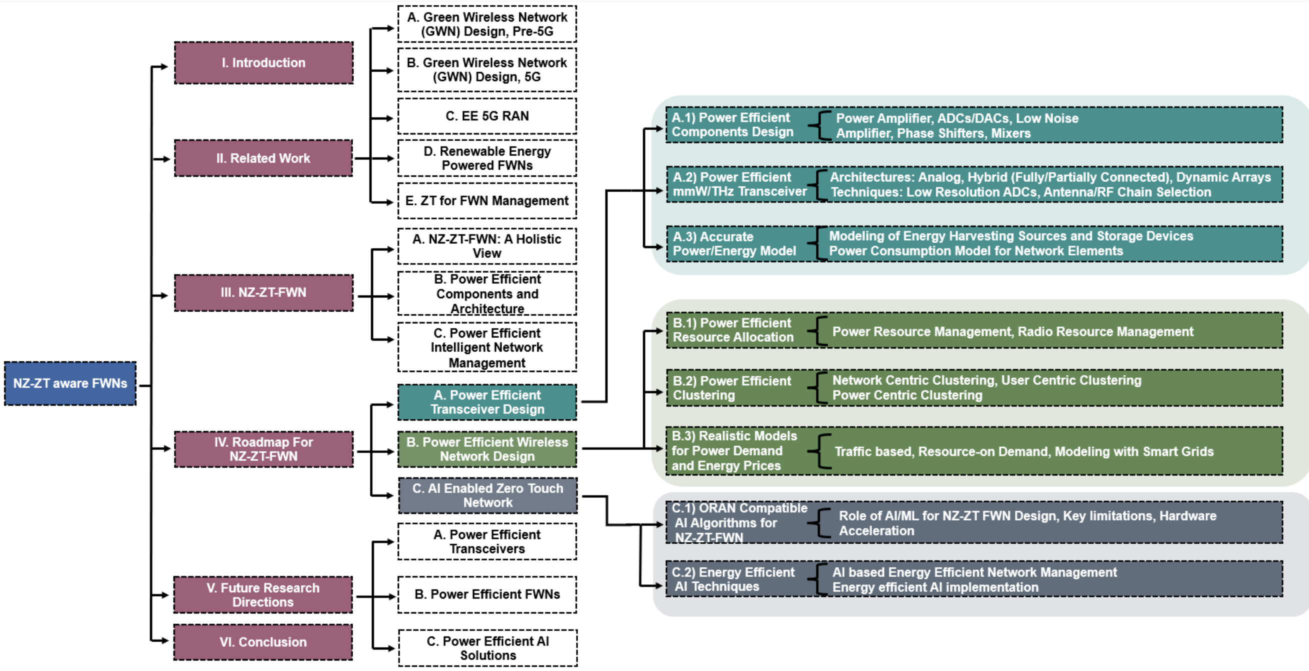

FIGURE 1. Taxonomy of NZ-ZT-FWNs along with the blocks illustrating the interconnection of research themes, forming a cohesive framework to accomplish NZ-ZT-FWNs.

essential part of FWN. These technologies will be leveraged with the potential benefits of Open Radio Access Network (ORAN), to provide implementation flexibility and Artificial Intelligence (AI)/ Machine Learning (ML) algorithms for predicting and optimizing network performance [12]. AI/ ML-enabled Zero Touch (ZT) resource management, will play a pivotal role in shaping FWNs towards NZ targets [5], [6], [7], [8], [9]. From this standpoint, this paper aims to identify key research areas that are essential for enabling *Net Zero - Zero Touch Future Wireless Networks* (NZ-ZT-FWNs). It is anticipated that achieving such networks would require significant research in developing accurate analytical models, orchestrating wireless network and smart grid resources, and designing innovative AI/ ML algorithms that align with NZ and ZT requirements.

Research efforts to achieve NZ and ZT objectives are mainly focused on three key aspects:

1) **Power Efficient Transceiver Design:** Power Amplifiers (PA)s and Analog-to-Digital Converters (ADC)s are known to consume a significant portion of power at both the transmitter and receiver ends. Trade-offs between power consumption, EE, and SE have been investigated in the context of mmW-MIMO receivers with low-resolution ADCs to identify power-efficient operating regimes [14]. Recently, it has been demonstrated that the maximum linearity region of a PA may not necessarily correspond to the maximum EE of the system [15]. Apart from that power efficient transceiver architectures have also been an active area of research.
2) **Power Efficient Wireless Network Design:** This area of research focuses on optimizing various aspects of the network to minimize power consumption. Topics such as network topology, cell size optimization, cell zooming, traffic management, resource management, BS cooperation, and smart grid resource management have been an active area of research [16].
3) **AI/ML-Enabled Wireless Networks:** AI/ML algorithms are expected to play a crucial role in harnessing intelligence in FWNs. Supervised, unsupervised, reinforcement learning, and game theoretic approaches have been employed in various scenarios, such as energy sharing in smart grid-powered wireless networks [17], resource sharing among end devices, edge and cloud [18], optimal resource management for renewable energy-powered small cell BSs [19], and game theoretic power management and cost optimization for green base stations [20].

These research areas are actively being explored to develop innovative solutions that can effectively reduce power consumption in wireless networks. However, further investigation is required to contribute towards the development of NZ-ZT-FWNs. This manuscript takes a significant step in this direction by comprehensively covering the key technologies, including, CFN supporting heterogeneous radio access technologies power by heterogeneous energy sources, THz communication, and AI/ML-based ZT-networks and highlighting the key limitations in the existing research and the possible future research directions that will pave a path towards the design of carbon neutral FWN.

The details of the different topics covered in this paper has been shown in Figure 1. Section I provides the introduction and motivation and highlights the three main aspects, namely, 1) power efficient transceiver design, 2) power efficient wireless network design and 3) AI enabled zero touch network, of NZ-ZT-FWN. Section II will extensively covers the related work and highlight the key contributions of this work. Section III will provide the overview of the envisioned NZ-ZT-FWN. Section IV is the core of this paper and will thoroughly discuss the key research areas that come under the umbrella of the three main aspects mentioned in Section I (see Figure 1). Section V will present a discussion on the open research areas. Finally, Section VI will provide the conclusion.

II. RELATED WORK

The research community has made significant efforts in developing various techniques and methods, leading to notable progress in achieving power-efficient wireless network design. The subsequent sections delve into specific areas of prominent progress.

A. GREEN WIRELESS NETWORK (GWN) DESIGN, PRE-5G

In [21], authors presented a detailed overview of the progress toward sustainable Fourth-Generation (4G) wireless networks. EE was quantified by considering a simple power consumption model focusing on BS powers for macro, micro, pico, and femto deployment scenarios and the trade-off between EE and other performance metrics, such as SE, throughput, bandwidth, and delay for different protocol layers was elaborated. Various approaches to improve EE of MIMO and cooperative relaying systems, such as dynamically changing the number of active antennas or Radio Frequency (RF) chains, relay selection, and impact of hop count were discussed in [22]. The EE management of cellular network BSs and Wireless Local Area Network (WLAN) Access Points (AP)s by exploiting dynamic resource management techniques such as BS/AP on/off switching and sleep modes was studied in [23]. These aforementioned research and references were mainly focused on pre-5G networks and did not address the issues related to the 5G and beyond wireless network design.

B. GREEN WIRELESS NETWORK (GWN) DESIGN, 5G

Potential techniques for improving EE of 5G networks were discussed in [24]. The authors highlighted the user-centric approach, also known as "no more cells", which has evolved into cell-free MIMO, as a means to improve the EE of the network through flexible network control. Moreover, the potential of mMIMO, full duplex communication, and cloud RAN was also reviewed. Focusing on 5G New Radio (NR), techniques to improve the power efficiency of 5G and beyond wireless communications were presented in [27]. This work mainly focused on power consumption reduction at the User Equipment (UE) and the BS and discussed techniques, such as sleep modes, bandwidth adaptation, and radio resource control in active states. In [25], alternative approaches for sustainable 5G communications that reduce carbon emissions without sacrificing the Quality of Service (QoS) are examined. These include utilizing energy harvesting techniques and employing renewable energy sources in ultra-dense sub-6 GHz, mmW, and mMIMO networks. The role of AI and ML in improving the EE of the 5G networks was highlighted in [26], where existing data-driven AI and ML-based algorithms in core, access, and edge networks were discussed and future research directions were identified.

C. EE 5G RAN

A comprehensive survey on the EE of 5G RAN with an elaborate discussion on RAN power consumption and EE metrics was provided in [28]. The authors also highlighted the performance of AI algorithms for current and future wireless networks. A detailed review of EE power control schemes for ultra-dense cell-free MIMO communication systems along with key limitations and future research directions with a particular focus on the power consumption model and EE maximization techniques were discussed in [29]. The aforementioned works and references therein primarily focused on designing EE 5G networks and did not discuss the efficacy of AI-based ZT automation solutions to achieve NZ FWNs. Moreover, the impact of recent technologies, such as Intelligent Reflecting Surfaces (IRS) [30] and THz [31] communication systems on energy consumption along with the impact of renewable energy sources to reduce the carbon footprint was not investigated.

D. RENEWABLE ENERGY POWERED FWNs

A detailed discussion on the renewably powered terrestrial and non-terrestrial wireless networks, key components, and notable topologies was provided in [16]. Solutions for efficiently utilizing renewable energy sources integrated with smart grids to power wireless networks, such as sleep modes and passive cooling were demonstrated to be beneficial for reducing the carbon footprint of FWNs [32]. Various aspects of renewably powered 5G and beyond networks, such as the feasibility of various renewable energy sources, energy harvesting techniques, efficient utilization of excess energy, and energy planning based on the pricing in smart grid system were discussed in [33]. In another work, authors surveyed renewable powered 5G networks [34] covering several aspects, i.e., the cooperation, configuration and dimensioning of the renewable energy sources, their integration in the smart grid and powering the cellular network. These aforementioned works did not focus in detail on the power consumption issues of THz communication systems and neither discussed the use of AI/ML for achieving low carbon footprint FWNs.

E. ZT FOR FWN MANAGEMENT

There have been some recent research efforts to exploit the potential AI/ML in improving the EE of wireless networks.

TABLE 1. Comparison of related research works with this article.

Related Work	Key Contributions	Limitations	Our Key Focus
GWN Pre-5G: [21]–[23]	Basic power consumption model for a 4G network is proposed. Discusses EE and SE trade-offs.	Role of 5G and FWNs has not been discussed.	AI-enabled NZ-ZT-FWN design.
GWN 5G: [24]–[27]	Proposes energy and power consumption model for massive MIMO. Discusses renewable energy sources.	Lacks discussion on THz communication and ZT approach.	THz communication and the role of ZT for FWNs.
EE 5G RAN: [28], [29]	Studied EE and power consumption with ultra-dense cell-free MIMO. Highlighted the importance of AI.	Did not study enablers such as THz, IRS, etc.	Investigating enablers such as THz, IRS.
Renewable energy solution: [16], [32]–[34]	Energy harvested sources and smart grid to reduce the carbon footprint of FWNs.	Lacks discussion on power consumption issues.	Examine power consumption issues to achieve NZ-ZT-FWNs.
ZT for FWN management: [36]–[42]	Feasibility of ZT-enabled network management and orchestration. Potential to improve SE and EE.	Partially addressed EE. Power consumption is not investigated.	ICT design for an NZ-ZT-FWN.

Network slicing and statistical federated learning-based approach to address the network management and orchestration challenges was proposed in [36]. The scheme achieved a 10× improvement in the EE compared to the state of the art. The authors in [37] have thoroughly investigated the role of AI to develop a green FWN by optimizing the energy management and radio resource management. In [38], authors provided a detailed survey on ZT network and service management while covering key architectures proposed by the standardization bodies and the role of AI to enable the ZT management. Authors in [39], presented a survey on end-to-end ZT network and service management, covering key aspects, including overview of ZT management architecture, related security issues, how ZT automation works, end-to-end service life cycle management, related standardization, the role of AI and future research direction. Focusing on the heterogeneous industrial network, the authors provided a review on the role of ZT network design leveraged with the potential of AI/ML [40]. In [41], challenges related to network slicing and AI algorithms that demand immediate attention have been highlighted. In a recent survey [42], ZT-based network management from RAN to the core network was investigated. However, the above works were focused on the potential of AI for future wireless network management without particularly addressing AI utilization for reducing the carbon footprint of the network.

Table 1 provides the summary of the related works by highlighting the key contributions and limitations, and that how this work distance itself from the existing literature. Although significant efforts have been put in to reduce power consumption in wireless communication systems, this paper highlights the substantial improvements required beyond state-of-the-art for NZ-ZT-FWNs. The paper discusses the key technologies and enablers including renewable power sources, smart grids, CFNs, μW/mmW/THz communication, ORAN, AI/ML and how these can be improved and integrated to achieve a NZ-ZT-FWN. The key contributions of this work are listed in Table 1 and summarized below:

- A NZ and ZT focused FWN design incorporating low energy consumption CFNs supporting heterogeneous technologies leveraged with mmW and THz communication, powered jointly with renewable and traditional energy sources that are supported with smart grid, and employing AI/ML-based network control has been investigated.
- The power and energy consumption concerns of NZ-ZT-FWNs are highlighted. Notably, a bottom-to-top approach has been adopted and the discussion encompasses the power and energy consumption/efficiency aspects across the entire spectrum, ranging from the bottom-level transceiver efficiency to the broader network-level perspective.
- The potential of AI/ML-based resource orchestration, leveraging the flexible ORAN architecture, for achieving NZ-ZT-FWNs has been emphasized. Furthermore, the crucial role of AI-based ZT automation in reducing the carbon footprint to realize NZ-ZT-FWNs is highlighted, accompanied by the identification of specific use case scenarios.
- Moreover, focusing on an up-to-date literature, network topology, placement and integration of network equipment with renewable energy sources to achieve NZ targets along with limitations of the existing approaches and potential future research directions have also been identified.

III. NET ZERO–ZERO TOUCH FUTURE WIRELESS NETWORK (NZ-ZT-FWN)

In this section, an outline of the envisioned design for NZ-ZT-FWNs is presented. The steps for achieving a power-efficient network are discussed along with the effectiveness of AI/ML algorithms and ORAN architecture for NZ-ZT-FWNs is examined.

A. NZ-ZT-FWN: A HOLISTIC VIEW

A holistic view of the envisioned NZ-ZT-FWNs is shown in Figure 2. It is anticipated that NZ-ZT-FWNs will be capable of supporting multiple radio access technologies including traditional microwave, mmW, and THz communication, and offer network access to multiple industry verticals, including traditional mobile communication, vehicle to everything (V2X) [43], [44], drone communication [45], and internet of things (IoT) [46]. However, the salient aspect of NZ-ZT-FWNs is that they will be powered in a hybrid fashion, i.e., with the traditional grid and renewable power sources such as wind and/or solar.

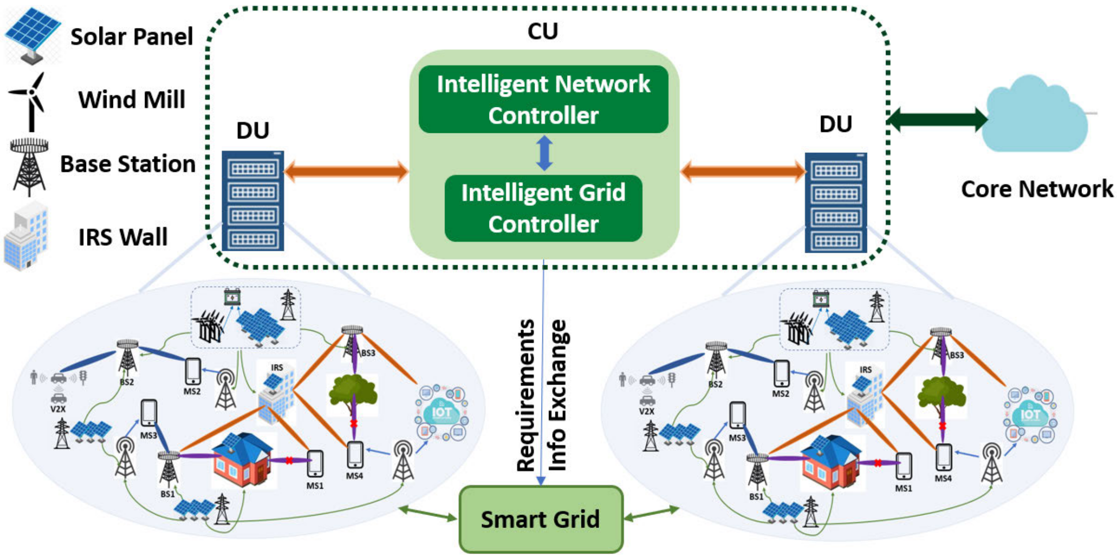

FIGURE 2. Envisioned NZ-ZT-FWN design, powered with renewable power sources and leveraging AI/ML-based optimization algorithms.

A smart grid controller will be responsible for efficient power distribution, while Distributed Units (DU), which may be collocated with Radio Units (RU)s, will handle computationally expensive tasks of the physical layer, Medium Access Control (MAC) layer, Radio Link Control (RLC) layer, synchronization, and radio resource management. Control Units (CU)s will be responsible for coordinating and managing multiple DUs and implementing higher-layer functionality of the 3GPP stack such as connection management, traffic flow management, encryption, and more. The CU will gather requirement information and interface with the RAN Intelligent Controllers (RICs) to intelligently optimize network resources using AI/ML algorithms. In NZ-ZT-FWNs, the CU will be responsible for an additional task i.e., exchanging information with the smart grid to optimize power usage within the network. Finally, it will also communicate with the core network via the backhaul link.

Building upon this framework, to achieve NZ targets, the design of NZ-ZT-FWNs should focus on, 1) power-efficient transceivers and architectures, and 2) AI-enabled approaches that can dynamically learn, predict, and adapt the network resources to save power. This necessitates an interdisciplinary effort encompassing power efficient circuit and component design, new transceiver architectures, integration of smart grids with renewable power sources, algorithms enabling power efficient orchestration of the power sources and efficient integration into the wireless network, and AI-based self-organizing solutions to dynamically optimize the network performance, as shown in Figure 3.

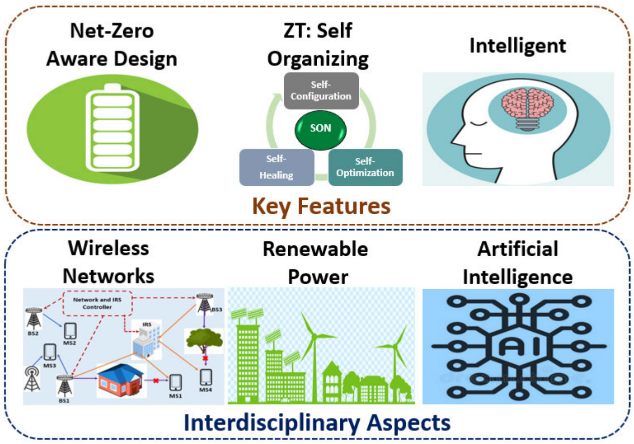

FIGURE 3. Interdisciplinary research aspects to reduce the carbon footprint of NZ-ZT-FWNs enables through intelligent network design.

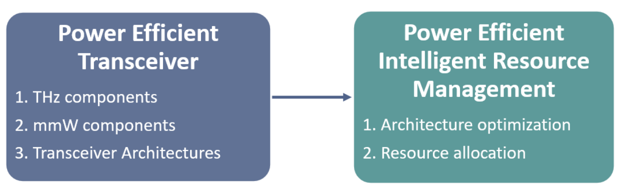

FIGURE 4. Power efficient NZ-ZT-FWN design flow from component to transceiver. Followed by a smart grid and renewable power sources FWN design.

B. POWER EFFICIENT COMPONENTS AND ARCHITECTURE

The overall research breakdown for a power-efficient NZ-ZT-FWNs is shown in Figure 4. The goal will be to optimize the network architecture focusing on designing optimal transceivers, placement of the power-efficient communicating nodes, resource allocation within the network, and renewable energy sources. Power-efficient transceivers are obviously an initial step towards NZ-aware wireless network design. This requires devising power-efficient mmW/THz components, precoding/combining algorithms, and transceiver architecture as shown in Figure 4. To further enhance the power efficiency of the network, it is imperative to strategically deploy the network nodes, enabling them to be powered by renewable energy sources and efficiently managed by smart grid controllers for power distribution.

C. POWER EFFICIENT INTELLIGENT NETWORK MANAGEMENT

NZ-ZT-FWNs are expected to be self-organizing with AI-based resource management being at the core of its design, due to three main factors, 1) 80% of network downtime is due to human errors, 2) manual configurations are prone to error and introduce additional delays, and 3) traveling of the trained personnel is not only expensive but also contribute to an increase in carbon footprint [47]. Furthermore, NZ-ZT-FWNs will comprise of multiple radio access technologies and frequency bands, posing a significant challenge for operators in terms of control and management. Therefore, AI-based automation will be necessary to address these complexities effectively.

As well as, the current RAN is comprised of vendor-specific hardware and software components that operate as black boxes which results in, a) restricted reconfigurability of the deployed RAN that limits the fine-tuning to address diverse traffic profiles and deployments, b) restricted coordination among components from different vendors and limits the joint optimization and c) vendor lock-in, that provides limited support to deploy and interface RAN with multiple vendor components [48]. ORAN addresses these issues by enabling open interfaces and intelligent network control to connect different components. Therefore, ORAN architecture enables the opportunity to automate, control and optimize NZ-ZT-FWNs through data-driven optimization [49], [50], [51].

Based on the above-mentioned advantages, it is foreseen that NZ-ZT-FWNs will be, 1) based on ORAN architecture with self-configuration, self-organizing and self-healing capability and 2) designed to be power efficient to reduce the carbon footprint, leading to NZ networks. However, significant efforts are required from the research community to make NZ-ZT-FWNs realizable. Now we will provide a thorough discussion on key research themes for NZ-ZT-FWN design.

IV. ROADMAP FOR NZ-ZT-FWN

Over the past few years, substantial research efforts have been dedicated towards diverse multidisciplinary fields such as power-efficient component design, accurate power consumption modeling for wireless networks, optimization of renewable-powered networks, AI-based intelligent algorithms for FWNs, and ORAN-based network control and design. Unfortunately, there has been a noticeable absence of research that specifically addresses network designs aimed at minimizing carbon emissions and promoting a low carbon footprint. Threfore, we have identified critical research areas that demand immediate attention to ensure the timely deployment of low-carbon footprint for NZ-ZT-FWNs. Figure 1 outlines the research themes and corresponding topics that will have a crucial role in achieving a NZ-ZT-FWN. The forthcoming discussion will delve into these areas in detail.

Firstly, Section IV-A covers the power efficient transceivers design aspects, and particularly, Section IV-A-I focuses on power-efficient component design, which serves as the cornerstone for developing a low-power Future Wireless Network (FWN). In Section IV-A-II, various approaches and techniques for power-efficient transceiver design will be explored, considering the integration of the previously discussed power-efficient components. These discussions aim to identify the most suitable methods for achieving energy efficiency in transceiver implementations. Section IV-A-III will focus on the development of an accurate power consumption model, which plays a critical role in optimizing both the transceiver and the wireless network for power efficiency. The availability of such a model is essential for effectively assessing and improving the energy efficiency and reducing the carbon emission of the system. Secondly, building upon the previous discussions of Section IV-A, Section IV-B will discuss power efficiency from wireless network design perspective. Particularly, Section IV-B-I will explore power-efficient resource allocation in a network design that incorporates heterogeneous power sources. This involves optimizing the allocation of resources to achieve maximum energy efficiency. In Section IV-B-II, the focus will shift to clustering techniques in the context of a network design that supports heterogeneous access technologies. Efficient clustering methods will be examined to enhance energy efficiency and performance in such networks. Based on the availability of power consumption models, transceiver and network design and knowledge about the traffic, a discussion on the realistic model for the power demand and energy pricing is provided in Section IV-B-III. Finally, AI enabled ZT wireless network design is covered in Section IV-C. considering the challenges and complexity associated with the FWNs design, ORAN and AI/ML will play a vital role to efficiently minimize power consumption. The role of ORAN along with AI/ML techniques to realize the design of NZ-ZT-FWNs will be discussed in Section IV-C-I. The discussion on energy efficient AI techniques is provided in Section IV-C-II. Overall, these sections contribute to extending the initial idea of a power-efficient network design to encompass heterogeneous power sources and diverse access technologies.

A. POWER EFFICIENT TRANSCEIVER DESIGN

Following a bottom-top approach, power efficient transceiver design will be a major building block for the NZ-ZT-FWN design. To this end, three key areas have been identified, namely, 1) power efficient component design, 2) power efficient mmW/THz transceiver, and 3) accurate power consumption model that will play a pivotal role in the design of power efficient transceivers and will be discussed in detail.

TABLE 2. Components with the performance metrics and limitation for mmW/THz Transceivers.

Components	Performance Metric	Limitation(s)
PAs	1. Power-added efficiency 2. Output power	Efficiency decreases with an increase in operating frequency
ADCs	1. Low power 2. Low quantization noise	Power consumption is proportional to bandwidth
LNA	1. Noise figure 2. Power consumption	Both metrics increase with the operating frequency
Phase Shifters	1. Insertion loss 2. A figure of merit (degrees/dB)	High insertion loss reduces the signal power
Mixer	1. Wideband support 2. Harmonic rejection	Designing a low-power mixer will be very important for THz

1) POWER EFFICIENT COMPONENT DESIGN

THz communication, carried out at a significantly higher bandwidth compared to the current 5G mmW systems, is considered a key technology for FWNs to enable massive terabits per second data rate [10], [52]. Despite the benefit of extremely high data rates, the power consumption of communication systems typically increases as we move towards a higher frequency spectrum. This is primarily due to increased interconnect, ohmic losses, and reduced device efficiency, therefore, designing low-power THz transceivers is an exceedingly challenging task. The key components of low-power mmW/THz transceivers and their limitations are summarized in Table 2 and discussed below.

Mixed-Signal Component Design: Mixed-signal components i.e., Analog-to-Digital Converters (ADCs) and Digital-to-Analog Converters (DACs) supporting gigabits per second sampling rate exhibit a significantly high power consumption [53]. The power consumption of an ADC is directly proportional to the operating bandwidth and the design of low power ADC, particularly, for the mmW and Thz receiver that are expected to support GHz of bandwidth will be very critical. Possible solutions are to incorporate low-resolution ADCs in the receiver design [14] or design power-efficient variable resolution ADCs [54].

Power Amplifiers: Power amplifier is an integral part of a wireless transmitter and is the most power-hungry device. Generally, the power-added efficiency (a figure of merit) of the power amplifier increases with the operating frequency. Recent research in PA design is mainly focused on the sub-THz band with a Power Added Efficiency (PAE) around 4% [55] which is lower than what has been achieved for PAs operating at mmW band [56].

Low Noise Amplifier Design: At the receiver, the design of a power-efficient Low Noise Amplifier (LNA) is of critical importance. Generally, the noise figure and the power consumption of LNA increase with the center frequency [57]. Therefore, for mmW/THz frequency, improved designs of LNA having a low noise figure and power consumption while supporting high bandwidth and gain require the focus of the research community.

Insertion Loss: Insertion Loss (IL) of a phase shifter degrades the performance which can be compensated by increasing the gain of the LNA at a cost of increased power consumption. To address this, there have been recent advances to reduce the IL of the phase shifter [58].

Mixer Design: Mixer is another important component of the RF chain. The design of a low-power mixer supporting wideband signals with the improved capability of harmonic rejection is also an active area of research [59], [60]. Apart from the aforementioned mentioned components, research on the power efficient design of other transceiver chain components operating at high frequencies should also be investigated.

2) DESIGN AND OPTIMIZATION OF POWER EFFICIENT mmW/THz TRANSCEIVERS

Utilizing power efficient transceiver components, there have been significant efforts to improve the efficiency of mmW transceivers using techniques that include: antenna selection [61], [62], [63], RF chain selection [64], [65], [66], low-resolution ADCs/DACs [31], [67] and by proposing power efficient multi-antenna transceiver architectures [68], [69], [70], [71]. These approaches are elaborated below.

1) *Antenna Selection* [61], [62], [63]: The best subset of antennas is selected (at the transmitter and/or receiver) to reduce power consumption, without compromising the SE of the system. Note that the traditional antenna selection techniques may not be feasible for high bandwidth FWNs.
2) *RF Chain Selection* [64], [65], [66]: The best subset of RF chains is selected and the RF chains that are not selected are switched off to save power. Although, this scheme has a drawback in that turning off RF chains significantly reduces the spatial multiplexing gain. However, it can be useful in off-peak times, where the traffic and data rate requirement is low, and therefore, switching off RF chains will result in power savings.
3) *Low-Resolution ADCs/DACs* [31], [67]: ADCs and DACs are considered power-hungry devices while operating at a very large bandwidth as in the case of mmW and THz communications systems. It has been shown that the low-resolution ADCs and DACs can significantly reduce the power consumption of the transceiver without any significant loss in the spectral efficiency of the system. Figure 5 shows the comparison of a digital and an analog receiver in terms of EE

TABLE 3. Main transceiver architectures and techniques to provide efficient solutions for NZ-ZT-FWNs.

Power Efficient	Options	Solutions
Architectures	Analog	1. Low power 2. Does not provide multiplexing gain
	Fully Connected Hybrid	1. Combines advantages of both digital and analog architectures 2. Consumes more power than an analog and less than a digital architecture 3. Achieves a lower data rate than digital architecture
	Partially Connected Hybrid	1. Consumes less power than a fully connected hybrid architecture 2. Achieves a lower data rate than a fully connected hybrid architecture
	Dynamic Arrays	1. Achieves a higher spectral/energy efficiency than a partially connected hybrid 2. Higher complexity as compared to analog structure
Techniques	Antenna Selection	1. Improves energy efficiency and reduces power consumption 2. Difficult to implement for wideband systems with frequency selective channels
	Low-Resolution ADCs	1. Significant power savings at higher operating bandwidths 2. Improves energy efficiency 3. How many bits should be used to maximize EE?
	RF chain Selection	1. Provides power savings and improves energy efficiency 2. Useful for architectures with a higher number of RF chains

vs a number of ADC bits. The scenario and power consumption model are the same as considered for Figure 7 (See Section IV-A-III *Simulation Comparison* for further details). It can be observed that there is an optimal number of ADC bits that maximizes EE. Therefore, it is possible to design an energy-efficient receiver with fewer ADC bits that would result in a significant power saving. Note that initially, the EE increases because the achievable rate increases at a faster rate with increasing bits, b, compared to the power consumption. However, after an optimal number of bits, EE decreases because now the power consumption increases at a faster rate. Furthermore, maximum EE is achieved by a digital receiver with a low-powered 5-bit ADC. A further increase in b mainly increases the power without significant improvement in the achievable rate. For instance, with a bandwidth of 1 GHz (a typical value for a millimeter wave communication system), the power consumption of an ADC (with the figure of merit set to 65 fJ/conv) for $b = 5$ and $b = 8$ is 2.1 mW and 16.6 mW, respectively. This difference will increase as we move towards the THz frequency band where the operating bandwidth will be around 10 GHz. Therefore, receiver design with low-resolution ADCs will be vital for power-efficient FWNs.

4) *Hybrid & Dynamic Architectures:* Several architectures such as fully/partially connected hybrid architectures and dynamic sub-arrays have been recently investigated [70], [71], [72], [73] to address the large power consumption and high implementation cost of the large antenna array systems. In a fully connected architecture, each RF chain is connected to all available antennas, and can generally achieve a spectral efficiency very close to a fully digital architecture. Partially connected hybrid architecture is a simplified form of a fully connected architecture where each RF chain is connected only to a subset of antennas. This results in power savings and a low-complexity design at the cost of a reduction in SE. In dynamic sub-arrays, RF chains are dynamically

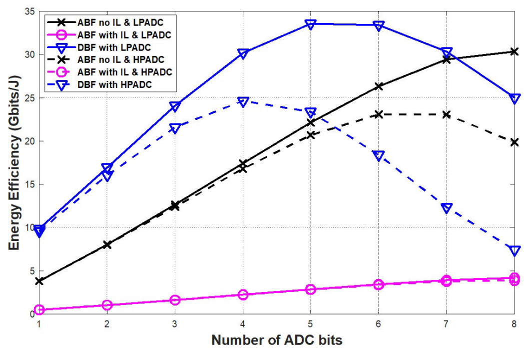

FIGURE 5. Energy efficiency comparison of an analog and a fully digital receiver with a low-powered and a high-powered ADC by varying ADC bits.

connected to antennas and improve EE and SE at the cost of an increase in system complexity.

The transceiver architectures and techniques that result in reducing the power consumption have been summarised in Table 3. In contrast to 5G mmW, future THz transceivers are expected to leverage ultra Massive MIMO with very large sub-arrays [74]. Recently, in [75], the authors provide a detailed power consumption model focusing on key transceiver components. However, the work on the power/energy consumption modeling for THz transceivers is very limited. Therefore, a paradigm shift in THz transceiver technologies motivates the researcher to rethink power and energy-efficient techniques to optimize transceiver performance.

3) ACCURATE POWER/ENERGY MODEL

An indispensable step towards achieving NZ-ZT-FWNs is to formulate an accurate power and energy generation/consumption model. This can be divided into two main aspects, i.e.,

(a) Modeling of energy harvesting sources and storage devices that can deliver the required power to the FWN.
(b) Power consumption of every network element.

These aspects are further elaborated below.

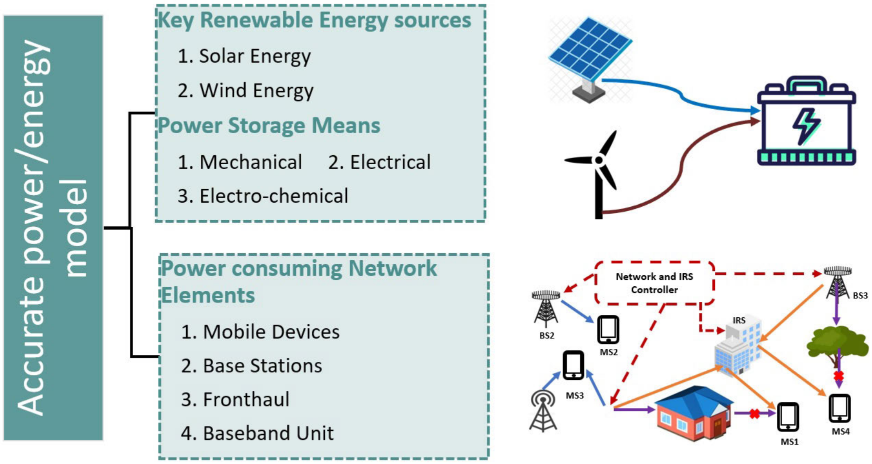

FIGURE 6. Key energy harvesting and storage devices and network elements.

a: ENERGY HARVESTING SOURCES AND STORAGE DEVICES

The two main candidates for renewable energy sources are solar and wind as shown in Figure 6. Solar energy sources can be placed close to the network whereas wind energy sources are expected to be deployed at a reasonable distance from the wireless communicating nodes due to their disadvantages, such as shadowing from the wind turbine blade [76].

Improving Efficiency: Efficiency is a key metric to measure the performance of wind and solar energy sources and quantifies how much energy from solar or wind has been converted into usable electrical energy. The efficiency of commonly available solar panels is between 15% to 22% [77]. Typical factors that affect the efficiency of solar panels include, 1) the type of the solar panel material, 2) inclination, orientation, and wiring of the system, 3) environmental factors, and 4) inverter efficiency. The energy generated by the solar cell array is given as [78]:

$$E_{Sol} = C_{Sol} \times P_{SH} \times k_{Sol} \times 365 \text{ days/year}, \quad (1)$$

where C_{Sol}, P_{SH} and k_{Sol} represent the capacity of the solar array (kW), peak solar hour, and derating factor of the solar array, respectively. Particularly, P_{SH} accounts for the location specific solar irradiance corresponding to the maximum sun shine value for a given number of hours while derating encompasses the impact of dust, wire losses, temperature and other factors that may lower the energy output of the solar array. Recently, researchers at National Renewable Energy Laboratory (NREL) built a solar cell that can achieve an efficiency of 39% [79].

On the other hand, for wind energy, Blitz showed that the theoretical limit for the achievable efficiency is nearly 59%. Recently, systems can achieve efficiency in the range of 20% to 50%, and thus, are close to the Blitz limit [80]. The average energy generated by the wind can be given as [81]:

$$E_{Wind} = \frac{1}{2}\gamma A_c \int_0^{T_i} S_w dt \quad (2)$$

where γ represents the density of the wind as a fluid, A_c corresponds to the cross sectional area through which the wind is passing, T_i is the time interval for which the is passing and S_w represents the speed of the wind.

While there is continuous improvement in the efficiency of renewable energy sources, further efforts are required from the scientific community to enhance this efficiency.

Energy Storage Devices: Energy storage devices are an essential requirement for renewable energy-powered systems as they store the surplus energy generated by renewable energy sources. This stored energy is then utilized to power the network. Energy storage devices can be categorized into mechanical, electrical, and electrochemical storage systems. The four key metrics of storage devices are storage capacity, energy density, power density, and storage efficiency. The study in [83] and [82], and references therein, discuss new approaches to further improve the performance of storage devices.

NZ-ZT-FWN will be a renewable energy system, comprising of and powered by renewable power sources and storage devices. The design and specifications of renewable power sources and storage devices are dependent on the power consumption requirements of the network elements. Hence, in addition to focusing on improving the performance of renewable energy sources and energy storage devices, deriving improved power consumption models is essential.

b: POWER CONSUMPTION MODEL FOR NETWORK ELEMENTS

To evaluate the carbon footprint of the different deployment strategies for NZ-ZT-FWNs, it is important to devise an accurate and tractable power consumption model. The current popular network deployment approaches are based on distributed and Centralized RAN (CRAN) [84]. Therefore, it is essential that the power consumption model is relevant to the deployment approach. For instance, in the case of a distributed RAN, the remote radio unit (RRU) and baseband unit (BBU) are placed at the same location whereas, in a centralized RAN, RRU and BBU are located at different locations, and connected via a fronthaul. Therefore, when developing a power consumption model for centralized RAN, it is necessary to account for the power consumed by the fronthaul link as well.

Power Consumption Model for RAN: In general, the power consumption of RAN, P_{RAN}, can be calculated as [28]

$$P_{RAN} = \sum_{i}^{I} P_{BS}^{i} + \sum_{j=1}^{J} P_{F}^{j} + \sum_{k=1}^{K} P_{V}^{k}, \tag{3}$$

where P_{BS}^{i}, P_{F}^{j}, and P_{V}^{k} represent the power consumption of the ith BS, jth fronthaul, and kth virtual BBU, respectively. The last two terms of (3) are specific to the CRAN architecture where the BBU is placed at a distance from the BS. Moreover, in 5G deployment, BBU may further be divided into DU and CU. Power consumption of the BS considering massive MIMO deployment, which is an indispensable component of NZ-ZT-FWNs, can be given as [85]

$$P_{BS} = P_{Tx} + N_{RF}^{TRX} P_{RD} + P_{NL}, \tag{4}$$

where P_{Tx}, N_{RF}^{TRX}, and P_{RD} represent the effective transmit power that accounts for the efficiency of the PA, number of RF chains, and the power consumption of the RF and the digital processing corresponding to each antenna branch, respectively. The number of RF chains, N_{RF}, is dependent on the type of beamforming architecture implemented at the BS. In general, $N_{RF}^{Analog} = 1 < N_{RF}^{Hybrid} < N_{RF}^{Digital}$, where N_{RF}^{Analog}, N_{RF}^{Hybrid}, and $N_{RF}^{Digital}$ are the number of RF chains in an analog architecture, hybrid architecture, and fully digital architecture, respectively. Hybrid architecture is a combination of both analog and digital architectures. Finally, P_{NL} represents the power consumption of the circuit that is not dependent on the load.

Power Consumption Model for Fronthaul Link: In a CRAN architecture, the signal from the RRU to the BBU is communicated using a fronthaul link composed of an optical transport network. Power consumption of the fronthaul depends on 1) the capacity requirements, 2) the number of BS deployed, and 3) the type of transponder. Based on these, the power consumption is calculated as [86]

$$P_F = \frac{C}{R_{Tr}} N_{BS} \left(2P_{Tr} + \frac{P_{port}}{N_{Wav}} \right), \tag{5}$$

where C, R_{Tr}, N_{BS}, and P_{Tr} represent the required transport capacity, transmission rate supported by the transponder, the number of base stations, and the power consumption of the transponder, respectively. N_{Wav} represents the number of wavelengths per fiber.

Power Consumption Model for VRAN: The performance of the CRAN architecture can be improved further through the Virtualization of RAN (VRAN), where the BBU resources are split and allocated in a virtualized manner. VRAN enables efficient resource allocation to tackle diverse user requirements and traffic conditions. In VRAN, intensive processing is shifted to the General Purpose Processors (GPP) which improve the EE. According to [87], the power consumption of a virtualized BBU, considering the GPP, the cooling system, and the dispatcher system is given as

$$P_V = P_{Co} + P_{DS} + P_{GPP}, \tag{6}$$

where P_{Co}, P_{DS}, and P_{GPP} represent the power consumption of the cooling system, dispatcher system, and general purpose processors, respectively.

Power Consumption Model for Transceivers: The power consumption of the transceiver plays a critical role in identifying the renewable energy source and battery requirement. BS transceivers are power-hungry devices composed of numerous intricately interconnected components and hardware. Consequently, to mitigate the overall power consumption, it is imperative to examine the power usage at the component level and subsequently identify suitable solutions to enhance the system's power efficiency. The power consumption of the transmitter and the receiver for a MIMO communication system can be computed as [75]

$$\begin{aligned} P_{Tx}^{Tot} &= N.P_{PA} + N_{RF} P_{UC} + P_{LO} \\ &\quad + 2N_{RF} P_{DAC} + P_{BBP}^{Tx}, \end{aligned} \tag{7}$$

$$\begin{aligned} P_{Rx}^{Tot} &= N.P_{LNA} + N_{RF} P_{DC} + P_{LO} \\ &\quad + 2N_{RF} P_{ADC} + P_{BBP}^{Rx}, \end{aligned} \tag{8}$$

where N, N_{RF}, P_{UC}/P_{DC}, P_{LNA}, P_{LO}, P_{DAC}/P_{ADC}, and $P_{BBP}^{Tx}/P_{BBP}^{Rx}$ represent the number of antennas, number of RF chains, power consumption of up/down converters, low noise amplifier, local oscillator, DAC/ADC and digital baseband processing unit at the transmitter/receiver, respectively.

More detailed models considering the power consumption of phase shifters, combiners, and splitters have also been investigated in other works [75], [86], [88]. One such receiver model will be discussed later. The above discussion provides a comprehensive framework to compute the power consumption of a cellular network. In addition to the aforementioned methodology, alternative models and approaches have been employed to assess the power consumption of cellular networks. For instance, in [88], a power consumption model was proposed, considering the varying power usage of macro, micro, and small cell BS deployments. Furthermore, the influence of functional split on the power consumption of the RAN architecture was examined in [86].

Simulation Comparison: Power consumption for a MIMO receiver is shown in Figure 7. The performance is measured with and without IL of the phase shifter and by varying the power of the ADC. For generating this plot, the figure of merit of the ADC is set to 65 fJ/conv and 494 fJ/conv for a low-powered and high-powered ADC, respectively [14]. The number of ADC bits are set to $b = 8$. IL is varied between 1 to 10 dB, and consequently, the gain of the LNA will be varied from 1 to 10 dB [89]. The power consumption of an

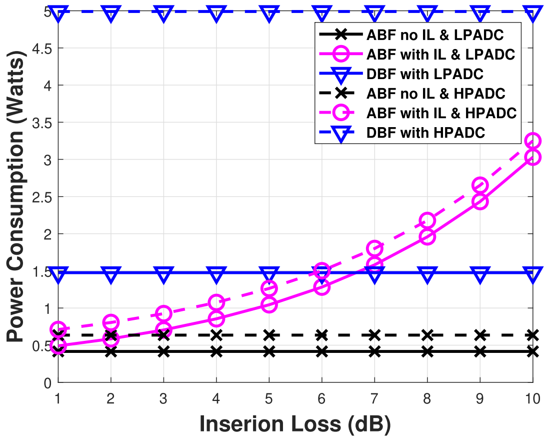

FIGURE 7. Power consumption comparison of an analog and a fully digital receiver with a low- and a high-powered ADC, with and without insertion loss (IL) of a phase shifter.

analog and a digital receiver is computed as:

$$P_A = N(P_{LNA} + P_{PS}) + P_C + P_{RF} + 2P_{ADC}, \tag{9}$$

$$P_D = N(P_{LNA} + P_{RF} + 2P_{ADC}), \tag{10}$$

where P_A and P_D represent the power consumed by an analog and a digital receiver, respectively. N represents the number of received antennas. P_{PS}, P_C, P_{RF} and P_{ADC} represent the power consumed by a phase shifter, combiner, radio frequency chain, and ADC, respectively. The power consumption of the LNA is computed as

$$P_{LNA} = \frac{G}{F(NF-1)}, \tag{11}$$

where G represents the gain, $F = 8.46\text{mW}^{-1}$ is the LNA figure of merit and $NF = 3.1$ dB is the noise figure [90]. The power consumption for the rest of the components can be found in [14].

In Figure 7, it should be noted that there is no impact of IL on the power consumption of the digital receiver architecture as it does not require phase shifters. Additionally, for comparison purposes, the power consumption of the analog architecture is plotted with and without IL. It can be observed that IL significantly increases the power consumption of an analog receiver. This is due to the fact that gain of the LNA should be increased to compensate for IL which results in an increase in power consumption. An analog receiver with no IL may achieve a lower power consumption than a digital architecture for both low-powered ADC and high-powered ADC cases. However, an analog receiver with IL, which is a more realistic model, consumes lower power than a digital architecture only for a certain range of IL, i.e., IL $<$ 6 dB. Therefore depending on the IL operating point, a design decision between an analog or a digital architecture can be made.

Power Consumption of Remaining Network Components: The preceding discussion highlights the importance of focusing research efforts on developing a comprehensive and realistic power consumption model that encompasses not only transceivers but also other network elements of NZ-ZT-FWNs, for example, IRSs as shown in Figure 6. IRS is an emerging technology that enables the creation of a programmable wireless channel adjusting the phase and amplitude of the incident signals, thereby enhancing signal quality and coverage by mitigating signal attenuation, multi-path fading effects, and interference [30]. The network power model must also take into account the power consumption of IRS technology and its associated components, including the IRS controller and the energy consumption impact of additional core network processing. This developed model can then be utilized to design and select suitable renewable energy sources.

B. POWER EFFICIENT WIRELESS NETWORK DESIGN

Based on the availability of the power efficient transceivers the next step is to integrate them into the network. The goal would be to ensure that this integration would result in a power efficient network design. Three main areas have been identified, i.e., 1) power efficient resource allocation, 2) power centric clustering, and 3) realistic models for power demand and energy prices, and will be discussed in detail.

1) POWER EFFICIENT RESOURCE ALLOCATION

The unprecedented increase in the data rate requirements and in the number of communicating devices will result in a highly complex network design [91]. Therefore, efficient utilization of network resources in renewable energy-powered networks will be a challenging task for NZ-ZT-FWNs. Particularly, network resource management is divided into two main tasks, 1) radio resource management [92], and 2) power resource management [93]. Resource management in wireless networks powered by heterogeneous energy sources is an active area of research [94]. However, a joint radio resource and energy management remains an open research area with significant potential for innovation [95]. Radio resource management mainly deals with power control, user scheduling, and QoS requirements. On the other hand, energy management emphasizes efficient resource management in terms of power among the network nodes. Several solutions for efficient power resource management have been proposed, such as cell zooming [96], energy trading [97], load control [93], energy cooperation [98] and switching off/on of BSs [99].

AI has been revolutionizing applications in every industry and vertical, including cellular networks and is envisioned to become the backbone of FWNs. Considering the highly complex nature of resource management, AI algorithms can be a main driving force for resource optimization [91]. Particularly, deep neural networks and Reinforcement Learning (RL)-based resource management solutions have been widely investigated [92], [95], [100]. Despite these research efforts, there are multiple aspects that require further investigation and will be highlighted in Section V.

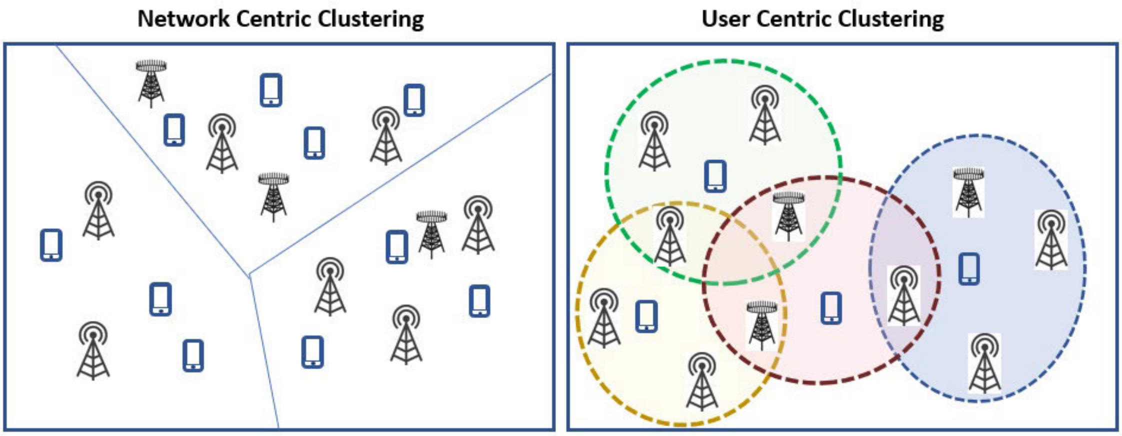

FIGURE 8. Network and user-centric clustering.

Case Studies: Now, two practical case studies will be discussed to emphasize the reduction in carbon footprint achieved in the practical cellular network deployment with renewable energy sources. A study on the solar powered BS deployment in Kuwait has been presented in [78]. In this study, the required number of solar panels, batteries, and converters are determined using HOMER software. Several different scenarios, including BS solely powered by diesel generator, solar, or by a combination of solar and diesel generator have been investigated. It is shown that the solar powered system resulted in zero carbon emission. Furthermore, CO_2 emission of a combined solar and diesel powered is only $4,713$ kg/yr whereas with a diesel powered system it reaches up to $80,746$ kg/yr. This highlights the importance of renewable energy sources to reduce the CO_2 of a cellular network.

In another work, solar and wind powered BS deployment in a rural area of Scotland has been investigated in [101]. The system is powered through solar and wind energy sources and the energy is stored in the battery bank. The battery bank system is integrated in the system so that the system operate without the availability of additional energy for M_D days while ensuring that the maximum capacity should not drop below the maximum discharge depth D_{Dep}, where $0 < D_{Dep} < 1$. Then, the relationship between the battery bank capacity B_C in kWh and the energy demand E_D in kWh is expressed as

$$B_C = \frac{M_D E_D}{D_{Dep}}, \tag{12}$$

while considering the total energy demand of 1.2 kWh, number of days without energy source $M_D = 3$ and that the stored energy should not drop below $D_{Dep} = 50\%$, the battery bank must store $B_C = 7.2$ kWh. Let, E_R represent the energy required per day to recharge the battery bank in M_R days, then the total energy production required from the renewable energy sources is $E_T = E_D + E_R$. For $M_R = 5$, the required $E_R = 720$ Wh, and therefore, the total energy production required per day is $E_T = 1.92$ kWh. It is shown that in winter solely the wind power can provide this energy, whereas in summer the wind energy generation reduces to 600 Wh. Then, the additional energy is supplied by the solar energy sources. This study highlights that heterogeneous energy sources will be essential to provide an uninterrupted energy throughout the year.

2) POWER CENTRIC CLUSTERING

Clustering allows to the division of mobile networks into distinct entities based on some criteria. Two popular schemes are, 1) network-centric clustering and 2) user-centric clustering are shown in Figure 8 [102], [103]. Networking-centric clustering has been adopted in 4G. The main disadvantage of this scheme is that there is a lot of interference to the edge users [104]. User-centric clustering has been proposed where a user is connected to all APs that can communicate with them with an SNR greater than a predefined threshold. User-centric clustering leads to CFNs, where for each user, there will be a region of APs that is overlapping with the region of other users [105]. Other protocols for user-centric clustering include limiting interference by creating service exclusion zones in which BSs are activated opportunistically to serve users [102], [103], [106]. Leveraging RL, it was shown that the size of service zones can be adjusted intelligently and dynamically to cater for service provision to diverse UE requirements [107]. Furthermore, K mean clustering has been proposed to minimize the effect of a strong interferer [108]. A graph partitioning-based approach has also been proposed to reduce the signaling overhead and complexity [109] while dynamic cooperation clustering has been considered in [110]. In contrast to the previous works, a promising area of research will be to further investigate the potential of power-efficient clustering in a mobile network.

3) REALISTIC MODELS FOR POWER DEMAND AND ENERGY PRICES

An accurate power consumption model provides an estimate of power consumed in a wireless network under normal operation. This model can be further enhanced by incorporating the power consumption in a high-load scenario along with varying energy pricing. The power consumed by a wireless network correlates with the amount of wireless traffic which varies with time and location [111]. Furthermore, its relationship with peak and off-peak energy prices has a direct impact on the capital expenditure and operating expenses for the mobile network operator [112]. Therefore, an optimization of the wireless network performance in terms of power and/or EE should also incorporate the cost-related constraints.

Predicting energy requirements based on the traffic load profile and how they correlate with the energy pricing will be important, not only to ensure efficient energy management but to minimize expenditures. This can be achieved by devising realistic power demand and energy pricing models. Recent research that caters to the economic aspects of wireless communications was mainly focused on enhanced mobile broadband. The dependency of throughput on the traffic demand in a large multi-cellular network was investigated in [113]. Particularly, stochastic geometry, queuing, and information theory-based approaches have been studied to predict and optimize network performance. Similarly, the problem of demand-driven power allocation using deep reinforcement learning has been recently addressed in [114]. In [115], authors proposed a game theoretic time-dependent pricing scheme for bandwidth scheduling. This motivates the users to free resources for delay-sensitive applications by shifting their delay-tolerant traffic to other off-peak time slots.

Extending the idea to renewable energy-powered networks, authors in [116], studied the cost efficiency of GWNs and showed that the GWNs can be at least two times more cost-efficient than traditional networks. Focusing on a network powered by heterogeneous energy sources, authors in [94] propose a resource-on-demand-based energy scheduling scheme for multiple cooperative RANs. Furthermore, a dynamic adaptive algorithm was developed for the efficient allocation of resources to reduce the power consumption cost of the grid. In [20], a game theoretic approach has been adopted to optimize the cost of 5G and beyond network operation. The availability of heterogeneous powered sources was considered where the BS reduced the energy cost through efficient operation consuming less power and selecting the supplier that had low generation cost. Author in [117] addressed the high energy consumption of 5G networks by utilizing solar energy sources. A mathematical model for photovoltaic systems, BS load, and energy storage systems was formulated to study and optimize the energy consumption cost of the network. Despite this, an effort from the scientific community is required to devise realistic models for power demand and energy prices.

C. AI ENABLED ZERO TOUCH NETWORK

Dynamic adaption and control will be essential for NZ-ZT-FWNs and traditional model-driven network management solutions may not be able to adequately address this aspect. To address this, AI enabled ZT network optimization will be indispensable. This aspect will be comprehensively covered in this section. Firstly, the need of ORAN supported by AI algorithms will be investigated. In addition, the key limitations will also be highlighted. Secondly, a thorough discussion will be provided on AI enabled power efficient network management along with the energy efficiency concerns related to the implementation of AI techniques.

1) ORAN COMPATIBLE AI ALGORITHMS FOR NZ-ZT-FWN

Network management encompasses several aspects, including, radio resource management, power resource management, low-energy radio resource scheduling, QoS optimization, BS activation and user association. To effectively handle these diverse tasks, the utilization of data-driven AI/ML techniques will be crucial, necessitating comprehensive end-to-end network management and control capabilities. However, the existing RAN architecture, characterized by its vendor-dependency and black box nature of network components (from the operator's perspective), lacks the capability to achieve end-to-end control, which is essential for attaining ZT automation for FWNs.

Moreover, the complexity of the network, diverse user requirements, the need for multi-objective goals, and the essentiality of end-to-end control for ZT automation all call for a transformation in RAN technology. To address this, an open-RAN (ORAN) architecture is envisioned as the paradigm to facilitate future ZT-network design [118], [119], [120].

In ORAN, the interfaces are open and standardized supporting virtual software-based control of the components, along with the flexibility of interoperability across different vendors. These features of ORAN provide the capability for end-to-end control, enabling implementation and execution of intelligent AI-based data-driven solutions to optimize the network performance and achieve ZT automation [48], [121]. Furthermore, disaggregation and virtualization of the network components provide flexibility in terms of network optimization and control. However, there are several open areas that need special attention to ensure the practicality and feasibility of AI-based ZT-ORAN deployment.

- *Lack of Data for Novel Network Architectures:* AI algorithms require data for training, validation, and testing. However, for any novel and new architecture, the experimental dataset will not be available until the deployment of the network. For instance, CFNs have not been widely deployed and thus, data is lacking for training AI models to optimize CFNs. Therefore, researchers need to explore approaches to generate representative synthetic data to augment the limited experimental data for model training and testing purposes. This can be achieved by simulating realistic network models that accurately capture

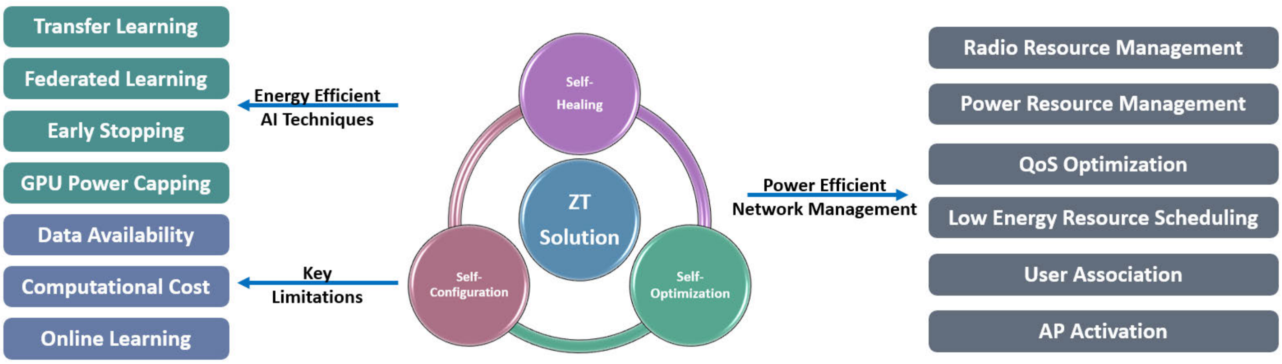

FIGURE 9. NZ-ZT-FWNs - Key research areas, limitations, and energy-efficient AI techniques.

the complexities of the network without relying on simplifying assumptions. Such simulations will require high computational processing power, which can be met by leveraging parallel processing GPUs. Another direction to consider is leveraging the capabilities of data augmentation algorithms and generative algorithms to generate new data points from the limited available data, thereby expanding the dataset and enhancing the training and model learning [122], [123].

- *Generalizable Models:* AI algorithms will be the backbone for network orchestration in FWNs and will be required to function for varying network deployments [124]. Therefore, a key research direction would be to devise AI-based solutions that generalize well and are easily transferable to optimize performance for different network deployments. Transfer learning (TL) and meta-learning-based approaches will play a key role to address this issue [125], [126].
- *Model Monitoring and Updating:* To ensure that the AI model is working correctly and not deviating or diverging, continuous monitoring and frequent updating will be crucial for future ZT deployments. This will enable reliable & robust end-to-end control and optimization of the network and prevent sub-optimal network behavior. Therefore, it is necessary to develop online learning algorithms that optimize the network without compromising performance.
- *Security and Privacy:* Secure communication in ORAN will be crucial, and federated learning-based techniques will play a critical role to address this issue [127].

Figure 9 highlights the key areas where the ZT approach will play a critical role along with key limitations in the current research and energy issues have also been highlighted. In summary, ZT solutions for ORAN-based architecture will be an enabler of end-to-end performance optimization by efficiently managing network resources and devising power-efficient solutions to achieve future net-zero targets. Below we present possible AI use cases to achieve NZ targets followed by the role of hardware acceleration techniques to improve the energy efficiency will be covered. Furthermore, a discussion on an energy efficient AI based network design will also be discussed.

a: DYNAMIC BS ACTIVATION/DEACTIVATION FOR POWER SAVING

BSs consume power continuously as they are transmitting control and data signals. Control plane signaling is broadcast in nature and consumes constant electrical power. On the contrary, data plane signals are transmitted on the shared channel, and the power consumption is mainly dependent on the traffic intensity. Moreover, continuous electric power is also being consumed by control circuits. In addition, operators are increasing the cell density by deploying more BSs to support an increase in the required data rate. All these factors contribute to the overall increase in network energy consumption, including the recurring energy consumption that is independent of the traffic load.

Consequently, during periods of low traffic loads, when the data rate requirement falls below the peak and network resources are underutilized, the BSs continues to consume continuous power, making the network power inefficient [128]. One possible solution to save power is to shut down BS(s) or cells based on a pre-configured scheduler. However, this approach has a drawback that it cannot dynamically adapt to changing traffic and network requirements and will significantly degrade network performance having a negative impact on UE QoS. This can be addressed by utilizing ML and RL-based adaptive ZT solutions which can dynamically sense the traffic requirements, learn, reconfigure and optimize the network, by activating/deactivating BSs to save power without compromising the QoS requirements of the user.

Recently, the problem of BS switching based on the traffic load to save power have been investigated [129]. Based on the historical data, dense neural network and recurrent neural network have been utilized to predict future traffic and select the BS sleep modes (on and off) accordingly. The proposed method has shown to decrease energy consumption by 63%. The concept of RL has also been employed to reduce energy consumption by optimizing BS sleep while simultaneously meeting QoS requirements [130].

b: HARDWARE ACCELERATION

Virtualization of network functions will be an integral part of the ORAN architecture. These network function are deemed to be executed on general purpose computer (GPU). Nevertheless, since these processing units are not specifically optimized for efficient network operations, their usage can result in higher energy consumption. Employing dedicated hardware can alleviate this issue of increased energy consumption. Furthermore, in contrast to software acceleration, hardware acceleration methods provide an energy efficient solution [131]. For instance, it is shown that the in-memory based hardware acceleration for bulk bitwise operation can result in a 35-fold reduction in the energy consumption.

Central processing units (CPU) with a multi-core system provide a possible option to implement network functions. However, in comparison to a single-core, multi-core systems consumes more power. To address this, power saving techniques, such as putting cores to sleep with no activity or reducing the voltage supplied to CPU, without compromising the performance should be investigated [131], [132]. Similarly, Field Programmable Gate Array (FPGA) based network functions implementation may result in a lower power consumption in comparison to a CPU based implementation [133]. It is shown in the literature that the FPGA based smart network interface card design is a feasible choice in terms of latency, cost and power [134]. For a detailed discussion on the hardware acceleration based energy reduction techniques references [131], [133], and [134] and references therein can be delved into.

2) ENERGY EFFICIENT AI

AI algorithms rely extensively on the availability of large datasets to train, validate, and test models. The process of transferring a substantial amount of data to the cloud leads to supplementary energy consumption [135]. Recent advancements in AI techniques have shown significant improvements in energy consumption. These enhancements by AI/ML requires an increased demand for computational resources, availability of powerful computing infrastructure, and specialized hardware for deploying AI/ML models [136]. However, this high-performance computing hardware requires significant power to operate and as a result, integration of AI/ML-based algorithms in the network will lead to an overall increase in power consumption of the developed system.

The potential of AI algorithms have been extensively explored to optimize the performance of a cellular network in terms of radio and energy resource management. In [137], network planning is proposed in a two step process. Firstly, Support Vector Machine (SVM) based regression is performed to estimate the required Physical Resource Blocks (PRB) per Mega Byte (MB). Then, focusing on minimizing the PRB per MB an improved BS configuration is obtained using genetic algorithm to facilitate cost and energy savings. In [138], a joint cell activation and user association scheme is solved using Q-learning approach to minimize the power consumption and backhaul load balancing in a dense heterogeneous network. The results showed a substantial improvement in term of energy efficiency and QoS. AI based approaches have also been investigated to optimize the power control in a single cell and a multi-tier heterogeneous networks where a global optimum is difficult to achieve [139], [140]. In [139], a reduced complexity branch and bound based scheme to maximize the energy efficiency is proposed which is then used to train a neural network. Authors in [140], highlighted the complexity in acquiring the global CSI in heterogeneous network and proposed a deep RL based approach where an AP can utilize a local deep neural network to optimize the power control. Focusing on a cloud RAN architecture, a joint cell sleeping and cooperative beamforming design while minimizing the power consumption in the network and satisfying the QoS has been considered in [141]. A deep neural network approach is proposed where the network trained to predict the beamforming vectors and sleeping mode based on the channel coefficients.

The energy management in a cellular network powered by heterogeneous energy sources is a complicated task and AI algorithms provide an efficient solution to address this issue. In [142], authors considered a two tier cellular network that was powered by the traditional grid and the solar energy. They proposed a distributed RL small BS switching approach to balance the energy consumption and network drop rate.

Although AI algorithms have been extensively explored to improve the energy efficiency of the network, the energy consumption associated with the training and deployment phase of these algorithms is also of an immense concern. Techniques, such as, federated learning, transfer learning, early stopping, hardware acceleration, and general purpose unit power capping, will play a vital role to limit the excessive power usage.

V. FUTURE RESEARCH DIRECTIONS

FWNs involves the integration of multiple technologies that corresponds to a highly complex design. Substantial efforts are needed from the research communication in multiple areas, i.e., right from the component to the complete network design, to make the NZ-ZT-FWNs a reality. This section comprehensively address that by highlighting the key research directions.

A. POWER EFFICIENT TRANSCEIVERS

Future research in this aspect can be divided into three key areas, i.e., 1) low power component design, 2) low power transceiver design and 3) accurate power/energy consumption model.

At the *component level*, PA and ADCs are the most power hungry components in the transmitter and the receiver chain, respectively. The design of a PA with a high PAE is of immense significance. Therefore, efforts from the research community are needed to devise novel techniques to improve the PAE. Possible low-power solutions and research direction can be to incorporate low-resolution ADCs in the receiver design or design power-efficient variable resolution ADCs that allow dynamically selecting the optimal number of ADC bits to ensure power savings without a significant decrease in the performance.

At the *transceiver level*, the research themes can be divided in to design techniques and architectures. Firstly, popular power efficient techniques includes antenna selection, RF chain selection and low resolution ADCs. Note that the traditional antenna selection techniques may not be feasible for high bandwidth FWNs. For instance, THz communication supporting 10s of GHz bandwidth will experience a high-frequency selective fading channel and a single antenna may not be sufficient to collect abundant signal power for reliable signal decoding. Therefore, this aspect requires attention from the researchers while devising antenna selection solutions. Similarly, RF chain selection depending on the channel characteristics and/or available traffic is worth exploring. Novel design architectures with low resolution ADCs or with variable resolution ADCs considering THz communication should be investigated. Secondly, analog and hybrid architectures are power efficient alternatives to a fully digital massive MIMO transceiver. Novel architectures that can result in further power savings should be explored. Thirdly, an integration of these techniques and architectures in an RIS assisted communication in a traditional and a CFN is a potential research area.

Accurate power/energy consumption model is of immense importance not only from a network deployment perspective but also to optimize the network performance with power constraint. A unified figure of merit that can be used as a benchmark to compare the power efficiency of various proposed designs and techniques will play a vital role. A recent effort in this direction can be found in [143]. However, the proposed metric can be improved by incorporating the power consumption associated with the baseband signal processing.

B. POWER EFFICIENT FWNs

From a network perspective, research efforts are needed in power efficient resource allocation, network clustering and realistic power/energy pricing models.

Resource allocation encompasses radio resource management and network resource management. To reduce the energy consumption of the network, there are key research areas that requires further investigation, such as:

1) Cell-free networks with extremely dense deployment supporting heterogeneous technologies.
2) Extremely high-frequency communication that would suffer from greater electronic distortion and would have different power consumption profiles.
3) High-complexity transceivers with an extremely large number of antennas.
4) MIMO muting, i.e., depending on the channel characteristics and traffic availability turning-off some of the MIMO features, and BS sleeping modes.
5) ORAN based self organized network design.

Therefore, multi-objective optimization to allocate power and bandwidth resources, perform user scheduling, ensure QoS, and distribute energy resources using a smart grid leveraged with AI-based algorithms will be worth exploring for aforementioned areas, particularly, in the context of NZ-ZT-FWNs. Moreover, most of the current research has been focused on the availability of perfect channel state information (CSI). Therefore, resource allocation with imperfect CSI is also worth investigating.

Network clustering with goal to reduce the carbon footprint is worth exploring. One key aspect would be to improve the power efficiency of the wireless network by optimizing the placement of RRUs and renewable power sources. Furthermore, it can be combined with user-centric clustering to study the trade-off and to identify a feasible hybrid solution that can take advantage of both techniques. Another option would be to form clusters with the goal to minimize the power consumption of the CFN subject to maintaining user QoS.

Finally, given the complex nature of FWN *realistic power/energy pricing model* should be developed with a particular focus on the technologies and use cases that are deemed for the future networks with a goal to not only reduce the power but to provide economic benefits as well.

C. POWER EFFICIENT AI SOLUTIONS

The research on reducing the energy consumption of AI solutions is a relatively recent development. *Federated learning*, which is a collaborative learning technique, can be one possible approach to reduce energy consumption [144]. As mentioned above, *transfer learning* will also play a vital role in reducing the energy consumption associated with the training of the AI model. Another possible option would be to terminate the training process as it approaches the optimal solution by tailoring the *early stopping* techniques [145].

There are several hardware based techniques have been proposed to reduce the power consumption associated with the AI/ML algorithms implementation. *Hardware accelerators* are necessary to solve the matrix algebra involve in the computations of NN training. The reliance on the high end CPU and GPU generally results in a higher energy consumption [146], [147]. Therefore, techniques such as, GPU cooperation and reduction in frequent memory accessing should be explored to ensure a power efficient implementation. In addition, research on *smart network interface cards* should conducted to reduce the energy consumption of the FWN [148]. *GPU power capping* method, which has been considered recently, can be interesting for future research to reduce the energy consumption associated with the training of the AI algorithms [149]. *Approximate computing* is another techniques to reduce the energy consumption but at the cost of a slight degradation in the performance due to the error introduced by the approximation [150]. This has been active area of research to ensure an energy efficient implementation of a neural network architecture [151]. However, the efficacy of approximate computing based NN implementation for scenarios where the reliability is of immense concern is an open area of research. With AI-based techniques serving as the foundation of future ZT wireless network design, it is imperative for researchers to not only enhance model accuracy but also focus on reducing computational complexity and energy consumption.

VI. CONCLUSION

This manuscript comprehensively highlights the key aspects of NZ-ZT-FWNs comprising joint renewable energy and grid-powered network architecture with a low carbon footprint. A detailed discussion about the different components of future networks from a power and energy consumption perspective has been provided. Furthermore, the current state of the art and future research directions have also been highlighted. AI-based solutions that can dynamically optimize the network to improve power efficiency and empower NZ-ZT-FWNs have also been discussed. Finally, future research directions are also highlighted.

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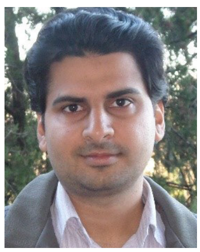

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