IEEE Open Journal of the
Communications Society

Received 3 July 2024; revised 29 July 2024; accepted 10 August 2024. Date of publication 14 August 2024; date of current version 23 August 2024.

Digital Object Identifier 10.1109/OJCOMS.2024.3443920

Device-Level Energy Efficient Strategies in Machine Type Communications: Power, Processing, Sensing, and RF Perspectives

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ABSTRACT The objective of our work is to provide an in-depth analysis and compilation of device-level strategies for enhancing the energy efficiency of Machine-Type Communication (MTC). The necessity for such strategies stems from the growing demand for sustainable and energy-efficient communication systems in various industries. We begin by presenting a comprehensive background on MTC, detailing its essential characteristics, the architecture of machine-type devices (MTDs), and their diverse applications. Next, we explore a range of energy-efficient techniques designed to optimize key subsystems of MTDs. These subsystems include the radio for communication efficiency, processing power for computational efficiency, and sensing subsystems for data acquisition efficiency. Each technique is evaluated for its potential impact on overall energy consumption and the trade-offs and limitations associated with these techniques are also assessed. In concluding, the paper highlights potential future research directions in this domain, outlining the ongoing need for innovative solutions to meet the escalating demands of energy efficiency in MTC.

INDEX TERMS Energy efficiency, Internet of Things (IoT), machine type communication (MTC), wireless sensor networks (WSNs), low energy consumption.

I. INTRODUCTION

IN RECENT times, a noticeable trend has emerged in the significant increase in the number of Internet of Things (IoT) devices, leading to a substantial rise in the production and dissemination of data through diverse communication networks [1], [2]. This proliferation of IoT devices has ushered in the necessity for communication networks with the capacity to accommodate machine-type communications (MTC), wherein low-power devices can autonomously exchange information [3], [4], [5]. According to the 3rd Generation Partnership Project (3GPP), MTC refers to automated applications and services that enable communication between machines without human intervention. Often used in the context of IoT, MTC includes diverse use cases such as smart metering, automotive telematics, remote health monitoring, and industrial automation [6]. The advent of 5G technology, and the anticipated 6G technology, play a pivotal role in addressing these evolving communication requirements, providing a robust framework for efficient and seamless connectivity for the burgeoning array of IoT devices.

The International Telecommunications Union (ITU) emphasizes improving energy efficiency in future International Mobile Telecommunications (IMT) systems including Beyond 5G (B5G) and 6G by integrating adaptive resource management and advanced technologies to minimize energy consumption. These advancements aim to ensure that enhanced capabilities are achieved sustainably, making B5G and 6G networks both energy-efficient and cost-effective [7]. The emergence of B5G and 6G technologies is poised to revolutionize the field of MTC, particularly regarding energy efficiency [5]. These next-generation

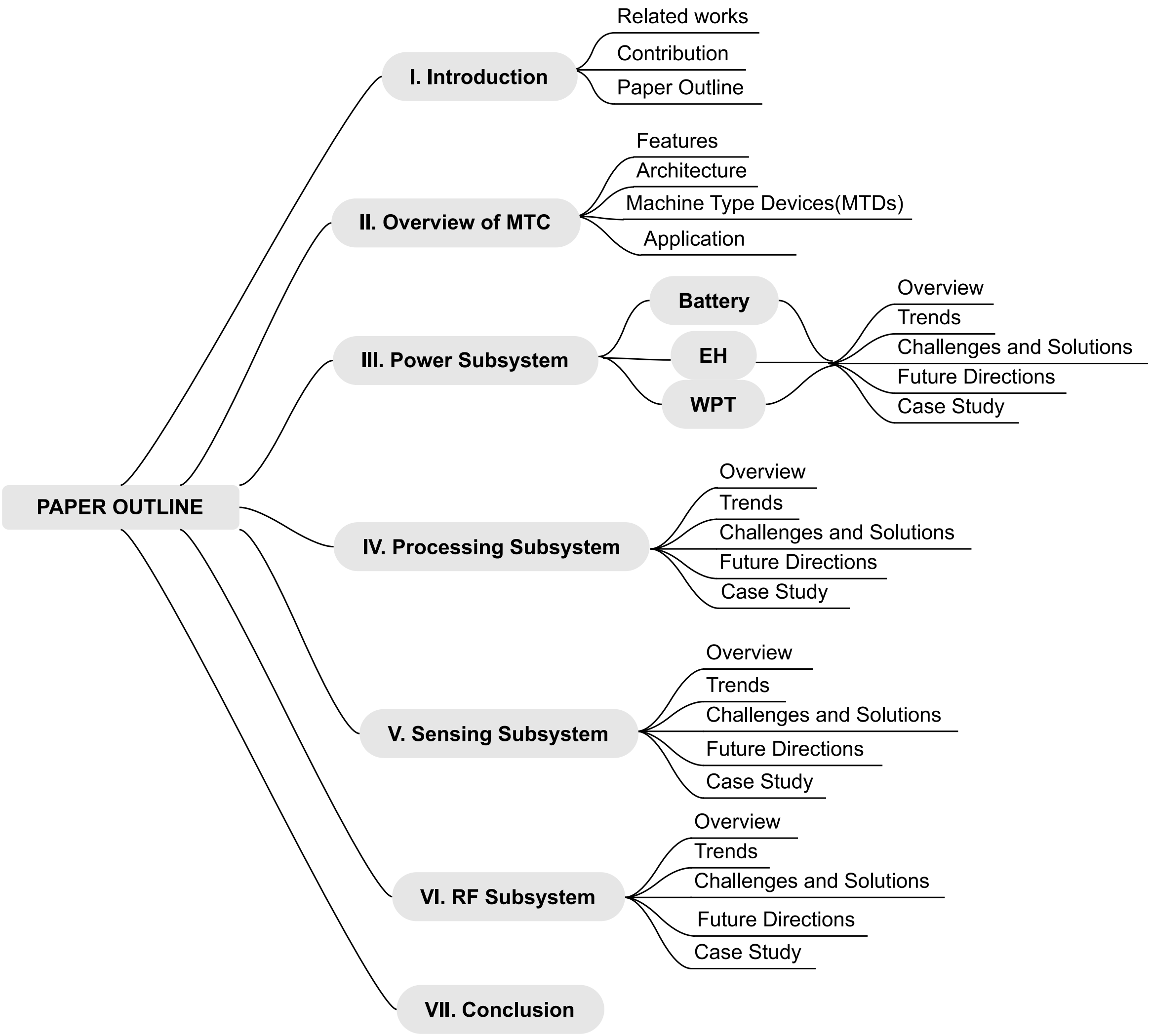

FIGURE 1. **Outline of paper.**

technologies are expected to deliver ultra-reliable, low-latency communication [8], [9], [10], [11], [12], [13], [14] with substantially higher data rates and increased network capacity, facilitating more efficient data transmission and reducing energy consumption associated with data processing and communication [15], [16], [17]. The integration of massive multiple input multiple output (massive MIMO) and beamforming techniques in 6G will optimize the energy usage of the radio subsystem by directing energy precisely, thereby minimizing wastage [18], [19]. A defining feature of 6G is the extensive use of artificial intelligence (AI) for network optimization [20], [21], [22], wherein AI and machine learning (ML) algorithms dynamically manage power consumption in MTC devices. These algorithms will enable real-time adjustments based on network conditions, traffic patterns, and device requirements, leading to substantial energy savings. Additionally, B5G and 6G will see the proliferation of advanced EH techniques such as ambient RF, piezoelectric, and thermoelectric EH [23]. These methods will provide sustainable energy sources for MTC devices, reducing reliance on traditional batteries [24]. The shift towards edge computing in 6G will facilitate data processing closer to the source of data generation, reducing the need for long-distance data transmission and consequently decreasing the energy consumption of MTC devices. Edge computing will also enable faster decision-making and lower latency, which are critical for energy-efficient operations in real-time applications. Thus, the introduction of B5G and 6G technologies will significantly enhance the energy efficiency of MTC by integrating advanced communication protocols, AI-driven power management, and innovative EH techniques. These improvements will lead to extended device longevity, reduced operational costs, and a lower environmental impact.

Among IoT devices, there exists a category of those that are batteryless [25], [26], [27] which provides potential and idealistic solution to power issues around deployment of IoT devices. Unfortunately, IoT devices that operate without batteries face constraints in terms of resources and possessing minimal power supply. Energy sources available

TABLE 1. List of acronyms.

Acronym	Description
Internet of things	IoT
Machine Type Communication	MTC
Machine Type Device	MTD
Wireless sensor network	WSN
Metal halide perovskites	MHP
Artificial intelligence	AI
Machine Learning	ML
Energy harvesting	EH
Body area network	BAN
Wireless Power Transfer	WPT
Analog-to-Digital Converter	ADC
Massive multiple-input multiple-output	Massive MIMO

for harvesting are often characterized by their weakness and unreliability, as the generated energy is contingent upon current environmental conditions (for instance, solar energy is not accessible during the night) [28]. Moreover, while in the dormant phase or during sleep mode, the device replenishes its limited energy reserves, especially when the capacitor has a small capacity [29]. These challenges maybe detrimental, especially for mission critical IoT services.

We primarily focus on battery powered devices which advance and confront their own set of benefits such as stable power [26] and challenges which include restricted battery capacity and computational capabilities. These challenges present difficulties when designing energy efficient communication networks [30], [31]. The concept of energy efficiency in MTC holds significant importance, especially considering that battery-powered MTDs are frequently utilized in remote or hard-to-reach areas [32], [33]. In such circumstances, optimizing energy efficiency at the device level becomes a crucial concern to significantly prolong the battery life of these devices without necessitating frequent battery replacements [34]. Furthermore, in densely deployed networks, the challenges of interference and congestion are heightened, leading to an additional surge in the network's energy consumption [35], [36], a condition which may excessively affect batteryless devices.

A. RELATED WORKS

Within the evolving MTC ecosystem, several scholarly works [37], [38], [39], [40], [41], [42] have scrutinized energy efficient techniques, each focusing on different aspects including power management and conservation in devices and communication networks.

Researchers in [37] provide a concise overview of Wireless sensor network (WSN), highlight factors contributing to energy loss, and introduce energy conservation approaches for effective power management. The paper explores particular schemes, including intermittent operation, methodologies based on data, and strategies based on mobility. Despite the extensive research discussed about, crucial concepts such as EH were not considered. In their work cited in [38], the authors provide a survey examining crucial energy efficiency techniques that classify the International Organization for Standardization (ISO) communication model into five distinct areas: enhancement of radio, reduction of data, sleep and wake-up strategies, and battery recharging. Energy efficient algorithms are also systematically compared and analysed and the research delves into various proprietary protocols and architectures. The work in [39] delves into the study of energy dissipation sources to identify novel solutions for energy conservation in the network. Furthermore, it offers a thorough summary of existing techniques for conserving and optimizing energy specifically designed for WSNs. The main approaches to energy conservation are introduced and classified into four primary categories: data-centric, intermittent operation, routing, and mobility-centric.

Recent energy efficient approaches designed for wireless systems based on green IoT are investigated in [40], particularly focusing on IoT-based heterogeneous WSNs at the core of IoT technology. The paper examines previous classification studies in the literature concerning conventional WSNs or networks based on IoT, emphasizing their main objectives and essential parameters. Subsequently, a comprehensive taxonomy that consolidates major energy conservation techniques for IoT-based WSN is also proposed in [41]. In their work cited in [42], the authors seek to underscore the significance of creating IoT technology that conserves energy and environmentally friendly approaches. The article introduces four framework principles for attaining energy efficiency in the realm of IoT, including MTC with enhanced energy efficiency, environmentally sustainable WSN, radio-frequency identification (RFID) systems optimized for energy consumption, and microcontroller units and integrated circuits designed for energy efficiency.

B. CONTRIBUTION

Although the current literature extensively examines the realm of energy efficient IoT which encompasses MTC and WSNs, a notable void has been observed. A review of the literature focused specifically on energy efficiency in MTDs remains strikingly absent. To address this scholarly gap, the contributions of this work are as follows:

1) For each subsystem, an extensive review of current trends in energy efficiency and innovations tailored for optimizing energy usage are presented. This includes of state-of-the-art technologies and strategies that have been specifically designed or adapted to enhance energy savings, such as energy-efficient sensing, low-power processing units, and advanced communication protocols. By focusing on these contemporary solutions, the review highlights the progress made in energy efficiency in each subsystem.
2) Challenges encountered in the implementation of energy-efficient strategies across different technological phases in each of the four subsystems such as high energy consumption, computational complexity, and hardware limitations are then discussed. The paper

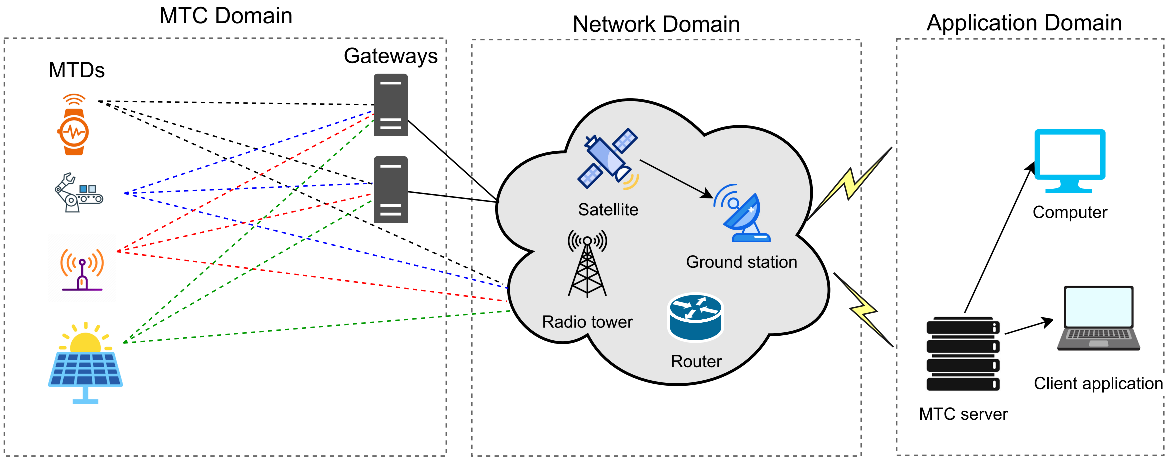

FIGURE 2. MTC architecture various the three domains depicted [3].

explores potential solutions, tracing the evolution from early technologies, which often faced basic limitations in efficiency, to current advancements that leverage sophisticated techniques like advanced modulation schemes, massive MIMO, and AI-driven optimization. By detailing these solutions, the paper provides a comprehensive overview of how technological progress has addressed and mitigated the energy efficiency challenges in each subsystem, offering insights into both historical and cutting-edge approaches.

3) A discussion of future directions for each subsystem, providing researchers with valuable guidance to foster innovation in MTDs. It offers subsystem-specific pathways for new research areas and technological advancements, aiming to drive further improvements in energy efficiency for MTDs. By highlighting these prospective directions, the work aims to stimulate future research and development efforts, ultimately contributing to more effective and sustainable solutions in the field of energy-efficient MTC.
4) A review of subsystem-specific case studies is incorporated to enhance the practical relevance of the work. These case studies provide real-world examples of how energy-efficient strategies have been successfully implemented. By analyzing these case studies, the work not only demonstrates the effectiveness of current technologies and methods but also highlights practical challenges and solutions. This approach enriches the theoretical insights with practical applications, offering a comprehensive understanding of how energy efficiency can be achieved in real-world scenarios.

C. PAPER OUTLINE

The structure of this paper, as illustrated in Fig. 1, is organized as follows: Section II provides a comprehensive background on MTC, detailing its essential characteristics, the architecture of MTDs, and their diverse applications. In Section III, the focus is on the power subsystem, discussing battery technologies, energy harvesting (EH) techniques, and wireless power transfer (WPT) methods to ensure sustainable energy sources for MTDs. Section IV explores strategies to reduce energy consumption in the processing subsystem, including low-power design techniques such as clock gating, power gating, and voltage and frequency scaling. Section V discusses techniques to optimize energy usage in the sensor subsystem, ensuring efficient data sensing and acquisition. Section VI examines methods to enhance the performance and power efficiency of the radio frequency (RF) subsystem, including modulation optimization, transmission power control, cognitive radio and energy-efficient communication protocols. Section VII provides the conclusion to the paper and summarizes the contributions of our research, highlighting subsystem specific trends and innovations in energy efficiency, challenges and solutions, future research directions, and practical case studies to demonstrate real-world applications and effectiveness.

II. OVERVIEW OF MTC

A. FEATURES

MTC encompasses various features that distinguish it in the realm of communication networks [36]. MTC involves the transmission of small packet data, where MTDs exchange short-payload data packets, such as meter readings within the network [6], [43]. MTC networks are engineered to accommodate a vast array of devices concurrently, offering scalability that extends to millions of devices within a square kilometer [44], thereby enabling expansive machine-to-machine (M2M) connectivity. MTDs also exhibit infrequent transmissions, with long intervals between consecutive data transmissions, depending on specific application requirements [45].

Importantly, MTC devices prioritize low power consumption, categorizing into idle, transmit, and receive states. The transmission frequency is adapted based on working conditions, minimizing energy consumption per device. This

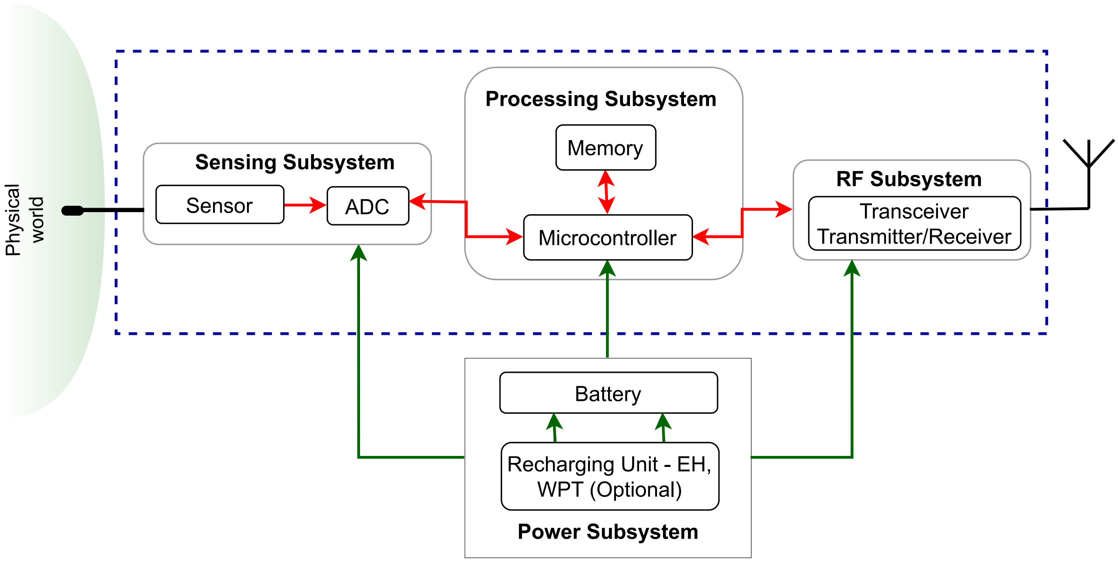

FIGURE 3. A depiction of the four key subsystems of a sensor node: power, processing, sensing, and RF. The power subsystem manages energy sources and consumption, data computation and control are handled by the processing subsystem, environmental data is collected and processed by the sensing subsystem, and the RF subsystem manages wireless communication and connectivity [33].

characteristic becomes particularly significant in ensuring long battery life for devices deployed in remote areas with limited access for recharging [13]. In extreme conditions, where recharging opportunities are restricted, the longevity of the MTD's battery assumes paramount importance.

B. ARCHITECTURE

The architecture of MTC is depicted in Figure 3. The architecture comprises three key components; the MTC domain, the network domain, and the application domain. It is a sophisticated framework designed to facilitate seamless communication between various components, catering to the unique requirements of MTD interactions.

The MTC domain includes a multitude of MTDs which are a category of devices that are capable of communicating over a network without human intervention. This includes sensors nodes, actuators and smart meters, or other specialized machines that are integral to specific applications [51]. Within the MTC domain, gateways or interfaces act as which act as data aggregation points between the MTDs and the broader communication network. The gateways themselves are equipped with intelligent capabilities, enabling them to effectively manage and organize the incoming sensory data. They are responsible for routing these packets of data through the most efficient pathways, utilizing either single-hop or multi-hop routes within the network domain, ultimately ensuring the delivery of data to the MTC server of the application domain. The MTDs communicate with the network domain by both direct and indirect access. Direct access involves MTDs communicating directly with the network domain infrastructure, while indirect access entails MTDs sending data through gateways before reaching the network domain.

The network domain serves as the backbone of MTC architecture [52], bridging the gap between the MTC device domain and the MTC application domain. Within this domain, a variety of protocols for wired and wireless networks, such as landline networks, WiMAX, and 3G/4G mobile networks, are employed. These protocols are specifically chosen for their cost efficiency and reliability, ensuring wide coverage for the seamless transmission of sensory information from the devices in the MTC domain to their intended destination in the application domain. In addition to these protocols, the network domain includes critical infrastructure components such as satellites, routers, ground stations, and radio towers, which facilitate data transmission and reception. Satellites are essential for global communication, especially in remote areas, while routers manage data flow between network segments, and ground stations connect satellite data to terrestrial networks. Radio towers ensure robust wireless signal coverage, creating a resilient network infrastructure that supports reliable information transmission within the MTC architecture. The application domain encompasses MTC servers responsible for processing and storing data received from MTDs. The MTC server functions as a consolidation point where all data from MTDs is stored, providing real-time monitoring data to various client applications for purposes such as smart system metering, electronic healthcare, and traffic monitoring [53]. Client applications utilize the processed data and together, these elements form a robust infrastructure enabling real-time remote monitoring and management, ensuring the efficient operation of diverse applications.

The focus of this work is sensor nodes which as discussed above, are one of the MTDs that make up the MTC device domain in a WSN. As outlined in the preceding section, the

TABLE 2. Energy efficiency requirements for the subsystems [46], [47], [48], [49], [50].

Subsystem	Energy Efficiency Requirements
Power Subsystem	High energy density (e.g., Li-ion batteries 250 Wh/kg), long shelf life (10 years), wide temperature range (-20°C to 60°C). Effective use of EH and wireless power transfer.
Processing Subsystem	Low-power operation,(active mode 5 mA, sleep mode 0.1 mA), efficient data processing (processing speed 100 MHz). Efficient volatile (SRAM access time 10 ns) and non-volatile memory (Flash memory density 1 GB). Lightweight OS for efficient task scheduling and resource management (e.g. TinyOS).
Sensing Subsystem	Low-power, high-accuracy sensors (e.g., temperature sensor 0.1°C accuracy, 10 μW power consumption), efficient ADCs (conversion rate 1 Msps). Techniques like data compression (e.g. compression ratio 4:1) and filtering to reduce the amount of data transmitted, conserving energy.
RF Subsystem	Energy-efficient modulation schemes (spectral efficiency 2 bps/Hz), transmission power control (output power -30 dBm), and low-energy communication protocols (e.g., LoRa, Sigfox, BLE). Use of standards that ensure reliable, long-range, and low-power communication (e.g., LoRa, Sigfox, BLE, NB-IoT).

realm of MTC encompasses a variety of endpoint devices, with particular attention given to wireless sensors within this review. According to [54], wireless sensors represent diminutive, battery operated devices, often referred to as nodes, possessing restricted storage, processing, and radio capabilities. The architectural configuration of a wireless sensor node is depicted in Figure 3. The nodes send data to the central node (the gateway) at the network's edge.

C. MACHINE-TYPE DEVICES (MTDS)

Each sensor node is a sophisticated system characterized by discrete subsystems collectively orchestrated to enable its seamless functionality. These subsystems are meticulously designed to ensure the sensor node's dependable operation across diverse environments. Table 2 summarizes the energy efficiency requirements for the power, processing, sensing, and RF communication subsystems of a sensor node, highlighting the need for high energy density batteries, efficient energy management techniques, low-power operation, accurate sensors, and energy-efficient communication protocols.

The power subsystem encompasses the energy storage component, responsible for storing harvested energy and providing a stable power source during periods of unavailability of ambient energy. In addition, the battery component is integral to this subsystem. In the processing subsystem, the microcontroller assumes the role of the core computational unit, while memory functions as the data repository, facilitating the storage and retrieval of data for efficient processing. In the sensing subsystem, the Analog-to-Digital Converter (ADC) undertakes the conversion of analog signals from the sensor into digital data, thereby facilitating compatibility with digital processing units. The RF subsystem, takes charge of managing radio frequency communication, efficiently handling signal reception and transmission.

D. APPLICATIONS

MTC applications span various domains, including smart cities, industrial automation, healthcare, and environmental monitoring. 3GPP specifications [6] emphasize the significance of MTC in enabling massive IoT (mIoT) applications, where large numbers of devices, such as sensors and actuators, communicate efficiently to support applications like smart metering, intelligent transportation systems, and remote health monitoring [64], [65]. In Table 3, we provide an analysis of the requirements for different subsystems of sensor nodes in various MTC applications, including smart cities, industrial automation, healthcare, environmental monitoring, agriculture, and transport where each application presents unique demands on the power, processing, sensing, and RF subsystems.

III. POWER SUBSYSTEM OPTIMIZATION

Power subsystem optimization is a critical aspect of research and development. MTDs are often deployed in environments where replacing or recharging batteries is challenging, making energy efficiency a key concern.

A. BATTERY

1) OVERVIEW

The body of knowledge regarding batteries is extensive and continuously developing, placing a significant emphasis on enhancing energy efficiency, prolonging battery lifespan, and investigating alternative technologies.

Various kinds of batteries are suitable for MTC devices, each presenting its own set of pros and cons [42]. These include, (Alkaline (ALK), Lithium Thionyl Chloride (LTC), Lithium Manganese Dioxide (LMD), Lithium Iron Disulfide (LID), Lithium Poly Carbon (PC), Lithium Cobalt Oxide (LCO), Lithium Polymer (LIPO)) used in MTDs. Non-rechargeable batteries like ALK and LTC are preferred for applications that require long-lasting power without the need for recharging. These batteries are typically used in devices where battery replacement is infrequent or impractical, such as remote sensors, medical devices, smoke detectors, and certain types of portable electronics. The longer shelf life, low self-discharge rates, and broad operating temperature ranges of these batteries make them ideal for environments where reliability over extended periods is crucial. On the other hand, rechargeable batteries like LCO and LIPO are designed for

TABLE 3. Applications of MTC and subsystem requirements [53], [54], [55], [56], [57], [58], [59], [60], [61].

Application	Power Subsystem	Processing Subsystem	Sensing Subsystem	RF Subsystem
Smart Cities [55], [56]	Prolonged battery lifespan, EH	Low-power microcontrollers and continuous data analysis	A range of sensors (motion, light, temperature)	Robust, energy-saving communication, LPWAN technologies
Industrial Automation [57], [58]	High-capacity batteries, commercial-grade EH	High processing power, low latency	High accuracy sensors (temperature, vibration)	Reliable, low-latency communication, industrial wireless standards
Healthcare [59], [60]	Energy-efficient, wearable devices	Real-time health monitoring and secure processing	High-accuracy biosensors (heart rate, glucose)	Secure, energy-efficient wireless communication, BLE
Environmental Monitoring [61]	Solar/wind EH, extended operational period	Low-power processors, effective data processing	High precision environmental sensors (humidity, pollutants)	Long-range, energy-efficient communication, LoRa, Sigfox
Agriculture [62]	Solar EH, long-term operation	Low-power processors for data analysis	Sensors for collecting soil moisture, temperature, and crop health data	Long-range communication, LPWAN technologies
Transport [62], [63]	High-capacity batteries, EH from vibrations	Real-time processing for traffic management	Motion, speed, and environmental sensors	Reliable, low-latency communication

applications that require recharging and typically have higher power densities. These batteries are ideal for devices with frequent usage and where recharging infrastructure is readily available, such as consumer electronics, electric vehicles, and mobile devices.

Mobile device batteries predominantly employ Lithium-ion (Li-ion) technology. Renowned for their high energy density, lightweight composition, and prolonged charge retention [46], [66], Li-ion batteries are the preferred choice for contemporary smartphones. On the other hand, MTD batteries encompass coin cell batteries, well-suited for low-power MTDs due to their compact yet durable nature [67]. These batteries are especially ideal for applications with minimal energy consumption. Additionally, lithium batteries are utilized in MTDs, sharing similarities with Li-ion but undergo optimizations tailored for low power requirements and extended standby periods [46]. Table 4 provides a detailed comparison of various battery types used in MTDs, focusing on key metrics like energy density, power density, internal resistance, nominal voltage, operating temperature, shelf life, and self-discharge rates while in Table 5 a comparison of technologies is provided.

B. TRENDS

With regards to MTD battery trends, the field is dynamic and new technologies and innovations continue to emerge. In [68] the study showcases the potential of metal halide perovskites (MHPs) for batteries with high capacity and EH devices and provides design insights for MHP-based devices. The work contributes to developing energy harvesters with high performance and storage devices. The role of technology for harvesting piezoelectric energy in the context of the fourth industrial revolution is discussed in [69]. It emphasizes the limitations of conventional batteries for powering IoT devices and highlights the potential of piezoelectric materials to convert mechanical and vibrational movements into electricity. The paper focuses on the progress made in the development of flexible energy harvesters for self-powered MTDs based on piezoelectric perovskite materials in the fields of biomedical and wearable technology in the past decade. AI is being used to optimize battery usage.

ML algorithms analyze data from MTDs to predict usage patterns and adjust power consumption accordingly, leading to more efficient use of energy. In [70], the study introduces an ML model using an algorithm for regression using random forests to predict the battery longevity of IoT devices. The significance of materials characterization in understanding electrodes of lithium-ion batteries and their constraints in performance is discussed in [71] where the potential of AI in addressing these limitations is also highlighted. The work in [72] is a critical review that examines the utilization of AI and ML methods in research on batteries. It discusses the ideas, methods, tools, results, and obstacles associated with using AI/ML to accelerate the development and enhancement of the upcoming generation of batteries–a current and significant topic in the field. The goal is to make these AI/ML tools accessible to the development and enhancement of the upcoming generation of batteries while ensuring completeness in covering various aspects of battery research and development.

C. CHALLENGES AND SOLUTIONS

1) EARLY TECHNOLOGIES

In the early stages of battery technology, nodes faced significant challenges due to the limited capacity and energy density of batteries [74], necessitating frequent replacements. The bulkiness and weight of these batteries also hindered the design and deployment of nodes, making them less practical for compact or portable applications. During this period, basic alkaline and lithium batteries were used as

TABLE 4. Comparison of non-rechargeable and rechargeable batteries [73].

Specification	Non-Rechargeable					Rechargeable	
	ALK	LTC	LMD	LID	PC	LCO	LIPO
Volumetric Energy Density (Wh/L)	506	1080	683	562	532	602	309
Weight Energy Density (Wh/kg)	176	480	323	300	300	217	185
Power Density (W/kg)	18	<0.1	6.5	300	0.3	650.2	123
Internal Resistance (mΩ)	<250	High	10-70	<350	<1000	∼40	∼40
Nominal Voltage (V)	1.5	3.6	3	1.5	3	3.65	3.7
Operating Temperature (°C)	-10 to 50	-55 to 85	-40 to 60	-40 to 60	-40 to 85	-20 to 60	-10 to 50
Shelf Life (years)	7-10	10	∼10	∼10	∼10	∼10	∼10
Self-Discharge (%year)	2–3	<1	1	2	0.5	12	60

solutions [75], offering modest performance improvements over older technologies but still constrained by capacity and longevity. Advancements in battery chemistry began to enhance battery life and capacity [76], marking the gradual evolution toward more efficient and durable power sources.

2) CURRENT TECHNOLOGIES

Current technologies in MTC focus on overcoming challenges related to battery depletion in remote and hard-to-reach locations [73], [77], which can be both costly and reduce operational reliability. Utilizing EH methods, such as kinetic and solar EH, is a key area of research, aiming to supplement battery power and extend the operational life of MTC devices [78], [79] by reducing dependency on battery replacements [80], [81], [82]. Lithium-ion batteries are popular due to their high energy density and long life cycles, yet finding a balance between compact size and energy density remains a challenge [83], [84]. Additionally, hybrid power systems combining batteries with supercapacitors offer improved performance and reliability [85]. MTC devices must also withstand harsh environmental conditions, prompting the design of low-power consumption techniques [86], [87], such as duty cycling [88] and energy-efficient protocols [89], to ensure sustainability and cost-effectiveness in the long term.

D. FUTURE DIRECTIONS

The future directions in battery technology emphasize the development of environmentally friendly, recyclable batteries to enhance sustainability. Research studies such as those in [90] and [91] focus on innovative, green manufacturing processes and advanced recycling technologies for lithium-ion batteries, addressing material recovery and environmental impact. Solid-state batteries, with their higher energy densities and improved safety, and the enhanced longevity of silicon anodes are highlighted in [92], [93], [94], [95], [96], [97], [98] as significant advancements. Additionally, flexible and lightweight battery technologies, including zinc-based and Li-S batteries, are being explored for their potential in wearable electronics and diverse device integrations, as discussed in [99], [100], [101], and [102], showcasing the progress in materials science and energy storage solutions for future applications.

E. CASE STUDY: BATTERY LIFE PREDICTION USING ML FOR ENVIRONMENTAL MONITORING

This study employes ML models to predict the remaining useful life (RUL) of lithium-ion batteries within MTC-based environmental monitoring systems [73], [103]. Equipped with sensors that continuously collect data on environmental parameters such as air quality and temperature, these systems utlize prediction models like Random Forest (RF), extreme gradient boosting (XGBoost), and long short-term memory (LSTM). By analyzing battery data, these models forecast lifespan, enabling proactive maintenance and optimized battery usage. Implementing ML for battery life prediction allows for timely maintenance and replacements, reducing unexpected failures and prolonging the operational life of sensors. This approach also lowers maintenance costs, especially in remote or hard-to-reach locations, ensuring continuous data collection and improving the reliability and effectiveness of environmental monitoring systems.

F. ENERGY HARVESTING

1) OVERVIEW

Efficiently optimizing the power module plays a critical role in the design and operation of MTDs. One promising strategy to improve the power efficiency of MTDs is the implementation of EH techniques which is as described by [104]. EH involves MTDs gathering energy from natural sources such as solar radiation and kinetic energy, utilizing ambient energy. Solar EH converts sunlight into electrical energy using photovoltaic cells. Thermal EH utilizes temperature gradients to generate electricity via thermoelectric generators. Kinetic EH converts mechanical energy from vibrations, motion, or pressure into electrical energy while RF EH captures ambient radio frequency signals and converts them into usable electrical energy.

Additionally, EH techniques can be categorized into two main architectures, as highlighted in [105]. The first is the Harvest-Store-Use Energy Architecture, which comprises three key stages: initial EH from the surroundings, subsequent storage of the energy harvested in specialized storage units such as batteries or capacitors, and finally, the utilization of stored energy to power electronic devices or systems. This method allows for the gradual accumulation of energy over time, creating a reservoir for consistent or

TABLE 5. Technology analysis [73], [77], [78], [80], [81], [82].

Category	Technologies	Description
Battery Materials	Metal Halide Perovskites (MHPs) Lithium-Sulfur (Li-S) Batteries	High-capacity batteries up to 500 Wh/kg and energy harvesters with conversion efficiencies over 20%. Energy density of approximately 2,500 Wh/kg, ongoing research in materials development, modeling, and control algorithms.
Energy Harvesting	Piezoelectric EH Solar EH	Converts mechanical and vibrational movements into electricity. Efficiency depends on the material properties, frequency of vibration, and mechanical design. Photovoltaic cells converting sunlight into electrical energy with power outputs ranging from milliwatts to watts per square meter. Conversion efficiency depends on factors like solar cell type (e.g., silicon-based, thin-film, organic), sunlight intensity, and environmental conditions.
Battery Optimization	AI and ML for Battery Optimization Materials Characterization	AI/ML algorithms to predict usage patterns and adjust power consumption, e.g., random forests for battery longevity. Understanding and improving lithium-ion battery electrodes using AI.
Advanced Battery Technologies	Solid-State Batteries Flexible Zinc-Based Batteries	Achieve energy densities of over 400 Wh/kg, improved safety, extended life cycles up to 10,000 charge-discharge cycles. Recent developments include fabrication methods achieving high flexibility and performance validation with specific capacities around 500 mAh/g.
Wearable Technology	Flexible and Wearable Batteries Nanotechnology in Batteries	Bendable batteries supporting wearable devices, offering specific capacities of around 200 mAh/g and maintaining performance over 1,000 bending cycles. Nanostructured materials such as silicon nanowires enhance lithium-ion battery components, increasing capacity and improving charge-discharge rates.
Sustainability	Sustainable and Eco-friendly Batteries Battery Recycling Technologies	Environmentally friendly and recyclable batteries, including biomass-derived anodes, bio-based separators, and non-toxic electrolytes. Advances in lithium-ion battery recycling technologies, improving sustainability and reducing raw material dependency.

TABLE 6. EH techniques [42].

Technique	Energy saving	Advantages	Disadvantages
Solar	70–90%	Sustainable energy source, abundantly accessible, applicable in remote regions	Relies on weather conditions (sunlight), initial equipment cost is high.
Wind	10–20%	Sustainable energy resource, applicable in remote locations.	Reliant on wind speed, initial equipment cost is high.
Kinetic	20–40%	Integrable with human activities, affordable initial equipment cost.	Kinetic energy sources have restricted availability.
Thermoelectric	5–10%	Requires minimal maintenance, lacks moving components.	Energy conversion efficiency is low, heat sources have restricted availability.
Electromagnetic	5–10%	Requires minimal maintenance, capable of harvesting energy from diverse sources.	Electromagnetic energy sources are not widely available.

intermittent power supply. In contrast, the second architecture, the Harvest-Use Energy Architecture, emphasizes the direct application of harvested energy without intermediate storage. Once energy is obtained from the environment, it is immediately harnessed to power electronic devices or systems. This approach offers a more immediate and continuous utilization of harvested energy, making it suitable for situations where live power generation and consumption are of crucial importance. In the rapidly evolving field of EH, various techniques have been developed to efficiently capture and utilize different forms of ambient energy. A summary of these techniques, extracted from [42], is provided in Table 6 and provides a description of EH techniques, highlighting advantages and disadvantages of each.

The trends in literature show that various studies address the challenges and advancements in EH systems, including power allocation algorithms, EH protocols, and the combination of EH and WPT. A summary of these technologies is presented in Table 7. Additionally, challenges such as unpredictable energy sources, limited storage, and the need for robust protocols are also highlighted.

G. TRENDS

Emerging developments in energy-harvesting approaches for sensors worn on the body and nodes within a body area network (BAN) are explored in [106]. The article begins by highlighting the human body's capacity for energy generation and then examines methods for harnessing kinetic and thermal energy derived from bodily movements, then it reviews various kinetic converters, including electromagnetic, piezoelectric, and triboelectric systems, examining their structures and performance. Recent advancements in EH systems for wearable technology, addressing the challenge of powering electronic devices are offered in [107].

The focus is also on methods leveraging the human body's heat and mechanical energy to enhance continuous operation, performance, and lifespan of wearables. In the study documented in [108], an iterative power allocation algorithm is introduced as a methods to improve efficiency of EH systems. An extensive examination of EH is provided in [109]. Furthermore, in [110], the research explores EH protocols that take into consideration the degradation of batteries. Additionally, as outlined in [111], certain techniques involve the integration of both EH and WPT. A comprehensive review of recent advancements in extremely low power techniques within EH-WSNs is presented in [112]. Another review that focuses on the coexistence of WPT and EH is available in [113] and [114], offering a comparative analysis of these technologies.

The critical challenges associated with energy management and conservation in EHWSNs are outlined in [112]. This presents the importance of developing EH-aware protocols and algorithms to ensure uninterrupted system operation. The discussed challenges include the unpredictable nature of energy sources, limited energy storage capacity, the need for efficient EH and management techniques, and the necessity for robust and adaptive protocols to manage energy availability and the operation of sensor networks. Challenges associated with traditional synchronization methods in WSNs due to resource constraints are addressed in [115]. Moreover, nodes deployed underwater encounter challenges related to limited power resources, as described in [116]. This paper proposes a control mechanism for underwater WSNs involving transmission power adjustment to enhance network performance.

H. CHALLENGES AND SOLUTIONS

1) EARLY TECHNOLOGIES

In the early stages of EH technology, devices faced significant challenges [127], including limited efficiency, bulkiness, and low power output [109]. Early energy harvesters, such as large solar panels and thermoelectric generators, could only convert a small fraction of available energy into electrical power, and their size made them unsuitable for compact sensor nodes. Additionally, their power output was often insufficient to meet the needs of modern sensor nodes, necessitating reliance on external power sources.

Solutions to these challenges included advancements in materials science [128], such as the development of more efficient photovoltaic [129] and thermoelectric materials [130], which improved energy conversion rates. Efforts were also made to integrate these energy harvesters into sensor nodes with a focus on reducing their size and enhancing efficiency through compact components. Moreover, the early adoption of small rechargeable batteries and supercapacitors addressed the issue of power output by storing harvested energy and providing a consistent power supply to the sensor nodes [131].

2) CURRENT TECHNOLOGIES

Current technologies in MTC focus on integrating EH components into devices without compromising their functionality, despite the challenge of limited space [117]. Advances in microfabrication and nanotechnology are essential in developing smaller, more efficient EH components that seamlessly integrate into MTC devices [118]. Advanced power management techniques, including sophisticated circuits and EH controllers with Maximum Power Point Tracking (MPPT) algorithms, help optimize efficiency and stabilize the power supply. Hybrid systems combining multiple EH methods, such as solar and vibration, offer a more reliable solution by enhancing overall energy capture across diverse environments. Efficiently managing harvested energy to ensure continuous operation is crucial, necessitating sophisticated energy management systems and algorithms to balance energy storage and consumption [119], [120].

I. FUTURE DIRECTIONS

Future directions in EH focus on scalability, environmental adaptability, and cost. Ensuring these technologies can effectively scale for large sensor node deployments is crucial, as is adapting them to perform well in diverse and harsh environments, such as extreme temperatures or low light conditions. Additionally, balancing the cost of advanced technologies with their benefits is essential for making them viable on a large scale.

Solutions to these challenges include leveraging nanotechnology [82] and advanced materials [122], [124], such as nanowire-based photovoltaic cells and advanced piezoelectric

TABLE 7. Technology analysis [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [82], [122], [123], [124], [125], [126].

Category	Technologies	Advantages	Disadvantages
Thermal EH	Body Heat, thermoelectric	Utilizes body heat, minimal maintenance, no moving components	Low energy conversion efficiency ($\sim$ 5-10%)
Energy Management	Iterative power allocation algorithm, EH protocols considering battery degradation, sophisticated energy management systems	Improves EH system efficiency, balances energy storage and consumption, extends battery lifespan by	Complexity in implementation, requires advanced algorithms
Integration of EH and WPT	EH and WPT Integration	Enhances efficiency, provides continuous power supply	Complex integration, may increase system cost
Renewable EH	Solar, wind	Sustainable energy sources, applicable in remote regions, solar energy density of about 100-200 W/m^2 per month, Wind energy density of around 50-150 W/m^2 per month	Dependent on weather conditions, high initial equipment cost
Microfabrication and Nanotechnology	Microfabrication for miniaturization, nanotechnology	Development of smaller, efficient EH components, seamless integration into MTC devices	Technological complexity, high research and development costs
Innovative EH Approaches	Greenhouse Gas Utilization, novel Piezoelectric Vibration EH, waterflow EH using piezoelectric materials	Advanced methods for clean EH, dignificant improvements over traditional methods, enhances efficiency and performance	Requires extensive research, may involve high initial costs

composites, which offer greater efficiency and versatility [123]. The development of smart materials that can dynamically adjust their properties based on environmental conditions also enhances EH efficiency. Furthermore, cost reduction strategies [121], such as exploring innovative ways to utilize greenhouse gases and different relative humidities to produce electrical energy, are critical for making these emerging technologies more accessible and practical for widespread use.

J. CASE STUDY: REMOTE PATIENT MONITORING IN RURAL AREA

The study in [125] and [126] focuses on the use of wearable devices to monitor vital signs, such as heart rate and glucose levels, especially in patients living in rural areas. The remote patient monitoring system employs wearable technologies powered by EH methods, ensuring continuous operation without frequent battery changes. These devices use Bluetooth Low Energy (BLE) technology to transmit real-time data to healthcare providers, enabling continuous health monitoring even in areas with limited access to medical facilities. The continuous collection and transmission of vital health data, is crucial for early detection and management of health issues. Thus, the use of EH methods to power wearable devices ensures their sustainability and reduces the need for frequent battery replacements, which is particularly beneficial in remote areas where access to reliable power sources can be limited.

K. WIRELESS POWER TRANSFER

1) OVERVIEW

WPT stands out as a technology with great potential [132] with significant potential to effectively address the energy constraints faced by portable battery-operated devices. This innovation enables the transmission of power through the air, proving particularly advantageous as the deployment of MTC continues to surge. The challenge of power supply becomes pronounced for many of these devices, often constrained by conventional power sources and necessitating frequent battery replacements [133]. This limitation adversely affects the scalability and efficiency of MTC deployment, underscoring the significance of WPT in this domain.

The growing demand for a seamless and sustainable power solution has spurred researchers and engineers to examine WPT technologies. By eliminating the need for physical connectors or frequent battery changes, WPT not only enhances the usability and convenience of MTDs but also contributes to the development of a more interconnected and efficient MTC ecosystem.

WPT itself can be broadly classified into two main types depending on the separation between the transmitter and receiver [134]:

1) *Far-field power transfer:* recognized as the radiative method, this type involves power transmission over longer distances. Examples of this include power transfer through radio frequency, microwave, optical, and ultrasonic technologies. However, due to the omnidirectional nature of radiative power transfer, the overall system efficiency is relatively low.

   The following section explores trends in literature on covering WPT, encompassing subjects like wirelessly powered sensor networks (WPSNs) and efficient energy transfer. It examines challenges related to WPT for advanced electronics, particularly in the context of biomedical implants. Another focal point is the implementation of wireless power transmission for

TABLE 8. Technology analysis [133], [134], [135], [136], [137], [138], [139], [140], [141], [142].

Category	Description	Advantages	Challenges	Applications
Electromagnetic Induction Technology	Uses electromagnetic fields to transfer power between coils	Widely used, effective for short distances	Performance affected by coil shape and coupling factor, limited range (up to 10 cm)	Long and short-distance electrical transmission
Microwave Power Transmission	Uses microwave radiation to wirelessly transmit power over longer distances	Facilitates wireless charging over longer distances, power levels up to several kilowatts	Safety and efficiency concerns at high power levels	Wireless charging, Smart houses
NOMA and SWIPT	Techniques that combine power transfer and data transmission	Efficient use of spectrum, Combines power and data transfer	Complexity in managing interference and EH	Relay networks, IoT devices
Dynamic and Adaptive WPT Systems	Systems that dynamically adjust to changes in parameters to maintain efficiency	High adaptability, Maintains system efficiency	Requires sophisticated control and management systems	Various WPT applications, IoT devices
Integration with Renewable Energy Sources	Combines WPT with renewable energy harvesting to provide continuous power	Sustainable, Reduces dependency on traditional power sources	Dependent on environmental conditions, Initial cost	Agricultural sensors, Remote IoT nodes

TABLE 9. Simulation parameters [137].

Parameter	Value
Number of samples	10^6
Distance of User 1 from BS (m)	1000
Distance of User 2 from BS (m)	500
Transmit power (dBm)	0-40
System bandwidth (BW)	10^6
Noise power dBm	$-174 + 10\log_{10}(BW)$

IoT devices, specifically utilizing microwave technology. Furthermore, there is research dedicated to the integration of wireless power technology into smart houses. An analysis of WPT technology is discussed in Table 8.

2) *Near-field power transfer:* acknowledged as the non-radiative method, this category encompasses power transfer over shorter distances. These methods rely on magnetic or electric field coupling, including capacitive and inductive WPT.

L. TRENDS

The paper by [134] provides a comprehensive examination of WPT, covering various implementation methods, underlying principles, and technologies employed for both long and short-distance electrical transmission. It places particular emphasis on the widely used electromagnetic induction technology and discusses factors affecting its performance, such as coil shape, coupling factor, and core material. In the realm of WPSNs and WPT, [133] focuses on reducing the need for battery replacement and minimizing energy consumption.

Meanwhile, [135] looks into the application of WPT systems for powering advanced microscale electronic devices, especially those used in devices for biomedical implants. The article highlights the challenges involved in designing efficient WPT systems, considering factors like system size, separation distance, operating frequency, and tissue safety. The primary objective of [136] is to implement wireless power transmission technology, particularly microwave power transmission, to facilitate the wireless charging of IoT devices. Additionally, the research paper [133] explores the integration of wireless power technology into a smart house using MTDs. It details the design and implementation of a wireless lighting technology utilizing microwave radiation, with the aim of wirelessly powering a 10W LED lamp at a distance of 50 meters within a smart house.

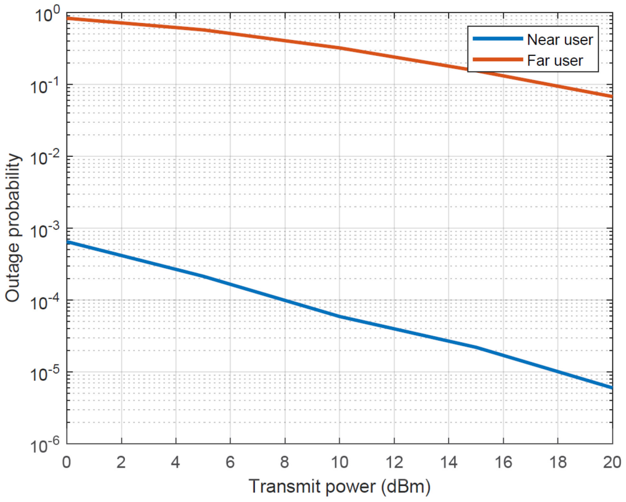

FIGURE 4. Outage probability for both the near and far users at various transmit power levels.

The main focus of [137] is to evaluate the performance of different relay selection schemes in a cooperate relaying

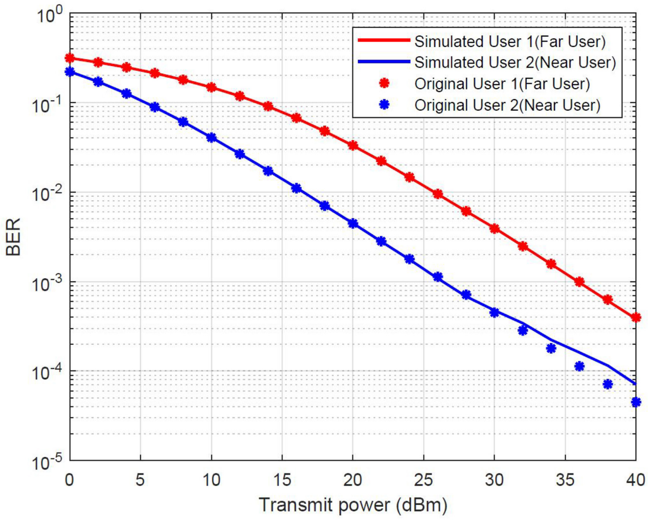

FIGURE 5. Comparison of BER between near user and far user.

system with non orthogonal multiple access (NOMA) and simultaneous wireless information and power transfer (SWIPT). The simulations are based on the parameters in Table 9. In the study, SWIPT is used to power the relays. The relay nodes harvest energy from the signal and used it to forward information to the other nodes in the network.

The plot in Fig. 4 illustrates the outage probability for both users. In the study, outage occurs when achievable rate falls below a specified target rate (1bps/Hz). The outage probability decreases with increasing transmit power because it leads to higher SNR which decreases the chance of achievable rate falling below the target rate. The far user generally has a higher outage probability compared to the near user reflecting that it is reliant on power harvested by the near user for communication.

Additionally, according to Fig. 5 which depicts BER for NOMA in AWGN, the far user exhibits a higher BER compared to the near user. This is because the far user performs successive interference cancellation (SIC). The far user must initially estimate the near user's data before executing SIC, and then accurately decode both the near user's and its own data. Thus the decoding errors from the near user will impact also its BER. Consequently, the far user ends up with a higher BER.

M. CHALLENGES AND SOLUTIONS

1) EARLY TECHNOLOGIES

In the early days of WPT, several challenges emerged, including low efficiency with significant power loss, very limited transfer distances of just a few centimeters, and the necessity for precise alignment between transmitter and receiver to maintain effectiveness [143]. Additionally, these systems were often bulky, expensive, and complex.

To address these issues, improvements in coil design and materials were implemented to boost efficiency [144], [145]. The advent of resonant inductive coupling enabled better efficiency over slightly longer distances by tuning both the transmitter and receiver coils to the same frequency [146]. Basic power management techniques were also introduced to convert and regulate the received power more effectively.

2) CURRENT TECHNOLOGIES

In current WPT technologies, several challenges persist, including maintaining efficiency and managing heat, especially in higher power applications [147]. Additionally, WPT systems can cause interference with other wireless communications and electronic devices [148], [149], while integrating WPT components into compact sensor nodes presents ongoing challenges in balancing efficiency and reliability.

Modern solutions include advanced resonance techniques such as adaptive resonant inductive coupling, which improve both efficiency and range [150]. Multi-coil systems and phased-array techniques enhance alignment and power transfer effectiveness [151]. Enhanced smart power management systems now offer better rectification, voltage regulation, and energy storage [152]. Furthermore, improved shielding and advanced frequency management techniques help mitigate interference problems.

N. FUTURE DIRECTIONS

Future directions in WPT focus on managing higher power densities while ensuring safety and efficiency, adapting to dynamic environments with varying alignment and distance, and integrating with compact IoT devices and wearables, which impose new constraints on size and efficiency [153]. Innovative power transfer methods such as laser-based power transfer [154] and advanced capacitive coupling [155] are being explored to overcome issues related to distance and alignment. Advances in microelectronics and materials science drive the miniaturization of WPT systems, facilitating their integration with compact devices. Smaller and more efficient WPT components are also being developed through materials science and nanotechnology advancements, utilizing nanomaterials and innovative fabrication techniques to create compact and efficient systems suitable for small MTC devices [142].

O. CASE STUDY: WPT FOR SOIL SENSORS

The study in [141] and [156], presents the implementation of WPT in agriculture involves using solar-powered and wireless-powered sensors to monitor soil moisture and other environmental conditions. A notable example is the use of UAVs to transfer power wirelessly to soil-based sensors, ensuring continuous operation without the need for battery replacements. This approach utilizes EH techniques to maintain sensor functionality, making it a sustainable and efficient solution for precision agriculture. The deployment of WPT in agriculture allows sensors to operate continuously without the need for frequent battery changes, reducing waste and environmental impact. Continuous power supply ensures that sensors can collect and transmit data in real-time, providing accurate and timely information to farmers.

Additionally, reducing the need for battery replacements and maintenance lowers operational costs, and real-time monitoring of soil conditions enables precise irrigation and resource management, improving crop yields and reducing water usage.

IV. PROCESSING SUBSYSTEM

A. OVERVIEW

Energy consumption in the processing subsystem of a node refers to the amount of electrical energy required by the node's processing unit to perform computational tasks. Various factors influence energy consumption in this subsystem, including the complexity of computations, data size, processor frequency, and system voltage. The energy consumption in the processing subsystem, denoted as [157], is given by:

$$E_p = L(S_i) \times V_{dc} \times I_{write} \times T_{write}, \tag{1}$$

where, E_p represents the energy consumption in the processing subsystem. $L(S_i)$ denotes the size of the data or the number of bits being processed. V_{dc} represents the DC voltage supplied to the processing subsystem. I_{write} denotes the current consumed during a write operation. T_{write} represents the time taken for a write operation. The processor subsystem is the central component that integrates other subsystems and additional peripherals within a system. Its primary function is to execute instructions related to sensing, communication, and self-organization. This subsystem comprises several key components:

1) *Microcontroller (MCU):* The MCU is the sensor node's central processing unit. It controls the overall operation of the node, executing embedded software that coordinates data acquisition, processing, and communication tasks [158]. It handles sensor data collection, processes the data locally, and manages communication protocols to transmit the processed data to a central server or cloud [47]. Popular MCUs used in MTC applications include ARM Cortex-M series, ESP8266, and AVR microcontrollers like the ATmega series.
2) *Memory:* The memory subsystem includes both volatile and non-volatile memory types. Volatile memory, e.g., SRAM, DRAM, is used for temporary data storage during runtime. Non-volatile memory, e.g., Flash, RRAM, FRAM, MRAM, PCM, is used to store firmware, configuration parameters, and collected data that must be retained even when the device is powered off [48]. These memory types are essential for providing the working space for the MCU to execute tasks, temporarily store sensor readings, and maintain data integrity and availability.
3) *Operating System (OS):* In some cases, sensor nodes may run a lightweight operating system that provides an abstraction layer for hardware access, task scheduling, and resource management [49]. The OS manages the execution of multiple tasks, handles interrupt processing, and provides APIs for interacting with hardware components. It simplifies application development by providing standard interfaces and services. Common lightweight operating systems for IoT devices include FreeRTOS, Contiki, and TinyOS.

B. TRENDS

Research in this area focuses on various aspects with topics that include the design of energy-efficient architectures, signal processing algorithms, data compression techniques, and low-power design strategies, summarised in Table 11. The emphasis is on improving the energy efficiency, computational complexity, and overall performance of the processing subsystems within energy constrained in wireless sensor nodes. The authors of [159] have developed an energy-efficient architecture for finite impulse response (FIR) filters in WSNs which are prone to increased computational load and energy consumption due to noise, leading to a reduced lifespan for sensor nodes. The proposed approach optimizes FIR filter design to minimize power and area requirements of the multiplier block and reduce the size of the look-up table. This work demonstrates significant reductions in both area and energy consumption compared to existing systems. In [160], an optimization of adaptive method for data reduction is introduced to decrease energy consumption in WSNs. This method utilizes two decoupled least mean square windowed filters of different lengths to approximate metric values at sink and source nodes.

The study in [161] explores the trade-off between communication and computation power in energy-constrained WSNs. It introduces an image compression scheme that is both low in complexity and energy-efficient that minimizes energy consumption while maintaining image quality through distributed processing tasks and adjusted transmission ranges. In [162], the authors propose data compression as an effective approach to maximize resource utilization in wireless networks. They present a set of compression algorithms specifically designed for WSNs, addressing the limitations imposed by limited resources. In [163], data compression techniques are explored to reduce energy consumption in battery-limited EH WSNs. By compressing sensing data packets, energy-rich sensor nodes contribute to conserving energy and extending the network lifetime. The study introduces an energy consumption model to analyze and optimize energy usage at each sensor node, along with a data compression algorithm tailored for EH WSNs. The work in [164] discusses a novel approach to deploying sensors in IoT application for environmental monitoring with a focus on reliability. It highlights the importance of solar EH to extend sensor lifetime and notes that temperature can greatly impact hardware reliability specifically low power MCUs and Raspberry Pi; and by accelerating failure rates.

The study in [165] reviews resistive random access memory (RRAM) technology, which is gaining attention in the field of next-generation memory technology due to its advantages such as fast and affordable and high density of storage. The work provides an in-depth look at various popular RRAM models, their switching methodologies, and how they relate to current-voltage characteristics in different prospective applications including non-volatile logic systems. Similarly the authors in [166] focus on the advantages of RRAM which include rapid operational speed, simple device architecture, minimal power usage, and scalability; features that make RRAM a strong candidate for replacing traditional memory technologies. The work in [167] examines compressive sensing (CS) and its application in power-efficient, real-time platforms for IoT applications. It evaluates existing literature and identifies emerging trends and future research directions for CS-based IoT systems. The challenge of maintaining quality of service (QoS) within strict energy budget constraints in wearables is acknowledged in [168]. The study explores approximation techniques to relax accuracy requirements, emphasizing the importance of leveraging error resiliency in IoT applications to maximize performance and energy efficiency. The need for improved IoT devices, sensors, and technology to enhance smart cities is emphasized in [169].

The article introduces approximate computing as a paradigm offering benefits in terms of space, duration, and latency, enabling efficient handling of a significant amount of sensed and processed data. In [176], the need for solutions with low complexity and compact size for managing visual data in IoT devices with constrained battery capacity is discussed. The proposed line-based compression system aims for visually lossless compression while reducing overall system power consumption through a combination of discrete wavelet conversion, adaptive line prediction, and compression techniques. Finally, the challenges associated with implementing complex energy-efficient algorithms without compromising functionality are highlighted in [177]. The text discusses the constraints in computational capacities faced by MTDs amidst increasing demands for more complex services and applications in state-of-the-art infrastructures.

The primary goal of the methods outlined below is to decrease the power consumption of MTDs by minimizing the frequency of transitions between high and low states. The following strategies, compared in Table 10, are employed to achieve low-power design:

1) *Clock Gating:* involves disabling the clock signal within a circuit block when it is not in use. The aim of the study by [170] is to recognize an efficient technique for synchronizing time among MTDs and minimizing energy consumption. They assess various existing clock synchronization approaches in WSNs and evaluate their impact on energy usage. Additionally, [178] introduce Synchronization through Piggybacked Reference Timestamps (SPiRT), a network architecture that reduces messaging overhead and minimizes energy consumption. It is worth noting that clock gating can reduce power consumption in sequential circuits but may affect circuit performance. Optimizing clock gating presents challenges such as minimizing the number of clock gating cells and balancing power savings and performance penalties.
2) *Power Gating:* refers to turning off power to a circuit block when it is not in use. A method demonstrated in [171] minimizes static power loss by gating power to individual functional blocks using power gates and power management units. Reference [172] investigate the influence of sensing hardware on overall power usage of an MTD and present power gating as a means to reduce power consumption at the circuit level. Their study shows a significant reduction in energy consumption. Additionally, [179] propose a low power consumption WSN protocol design. Power gating deactivates leakage currents in inactive functional units, which is examined in detail in the paper by [173].
3) *Voltage and Frequency Scaling:* reduces the supply voltage to a circuit block, while frequency scaling reduces the clock frequency of a circuit block. Reference [180] explore the implementation of Dynamic Voltage and Frequency Scaling (DVFS) methods to lower the energy consumption of a microcontroller in a sensor node. A combined energy management approach employing a combination of DVFS and duty cycling techniques, aiming to reduce the energy usage of the radio communication module is presented in [175]. The focus of [31] is on the impact of dynamic scaling, including voltage and frequency adjustments, on reducing energy consumption in MTDs. Similarly, [171] analyze the effect of voltage scaling on MTD components and aim to optimize dynamic voltage scaling for a microcontroller by incorporating it and dynamic power management. Reference [181] present an algorithm, Feedback Dynamic Voltage Scaling, that enhances the energy efficiency of WSNs by minimizing energy consumption while maintaining real-time tasks. Finally, [182] propose a power utilization optimization strategy, Hybrid Energy-Efficiency Power Management Scheduling based on dynamic power management and DVFS, demonstrating the effective dynamic scheduling of tasks to utilize available energy. The limitations of conventional computer-aided design flows for DVFS designs, emphasizing the need for energy-efficient systems that are not constrained by their energy consumption, especially in MTDs with limited processing capabilities are described in [174].

C. CHALLENGES AND SOLUTIONS

1) EARLY TECHNOLOGIES

In the early stages of IoT sensor node development, several significant challenges emerged. Limited processing power of early MCUs restricted the complexity of data processing algorithms, while inefficient power management resulted

TABLE 10. Comparison of low power design strategies [31], [170], [171], [172], [173], [174], [175].

Technique	Advantages	Challenges	Applications
Clock Gating	Reduces dynamic power consumption by turning off unused clock signals, can be applied at multiple subsystems.	May impact circuit performance due to added delay, requires careful timing analysis to avoid glitches.	Microcontrollers and processors in IoT devices, digital circuits in embedded systems.
Power Gating	Reduces static power consumption by turning off power to inactive blocks, helps manage leakage currents.	Adds complexity to power distribution and management, may require additional power management units.	Low-power designs for microcontrollers and SoCs, energy-efficient sensor nodes in IoT.
Voltage and Frequency Scaling	Reduces energy consumption by scaling down supply voltage and clock frequency, offers flexibility in managing energy vs. performance trade-offs.	Requires sophisticated control systems for dynamic adjustments, potential stability issues at lower voltages.	Processors in mobile devices and laptops, sensor nodes in IoT and MTC applications.

TABLE 11. Technology analysis [159], [160], [161], [162], [163], [164], [165], [166], [167], [168], [169], [170], [171], [176], [177], [178], [171], [172], [173], [174], [175], [179], [180], [181], [182], [183], [184], [185], [186], [187], [188], [189], [190], [191].

Category	Technologies	Advantages	Challenges	Applications
Energy-efficient Architectures	Finite Impulse Response (FIR) Filters, low-power design strategies	Significant reductions in area and energy consumption, reduces dynamic and static power consumption	Increased complexity in design, adds complexity to power distribution and management	WSNs, embedded systems
Signal Processing Algorithms	Low complexity set membership channel estimation algorithms, compressive sensing (CS)	Reduces computational complexity, efficient data acquisition and processing, power-efficient real-time platforms	May affect accuracy and performance, maintaining quality of service (QoS) under energy constraints	WSNs, IoT applications
Data Compression Techniques	Adaptive data reduction methods, image compression schemes, data compression algorithms for WSNs	Decreases energy consumption, balances energy consumption and image quality, improves network energy efficiency	Complexity in implementation, maintaining image quality, limited resources for complex algorithms	WSNs that are energy constrained
Memory Technologies	Resistive Random Access Memory (RRAM)	Fast operation (write time of 0.3–30 ns, read time of 20 ns), low power usage	Development and integration challenges	Next-generation memory technology, non-volatile logic systems
Battery and EH	Battery-limited EH WSNs	Optimizes energy usage, extends network lifetime	Limited energy sources, maintaining battery health	Environmental monitoring, IoT applications
Approximate Computing	Approximate computing, low-complexity visual data management	Efficient handling of large amounts of data, reduces energy consumption, visually lossless compression, reduces system power consumption	May compromise accuracy, complexity in achieving lossless compression	Smart cities, IoT devices with constrained battery capacity.

in short battery life, curtailing the deployment duration of sensor nodes. Communication constraints [192] were evident as early wireless protocols were not optimized for low power, leading to high energy consumption during data transmission. Additionally, limited RAM and non-volatile memory capacity restricted the amount of data that could be stored and processed locally.

To address these challenges, developers focused on creating lightweight algorithms [193] tailored to fit within the restricted computational resources. The introduction of low-power MCUs and communication modules [194], [195] helped extend battery life. Furthermore, data compression techniques were utilized to minimize the amount of data transmitted, thereby saving energy and enhancing overall efficiency [196], [197].

2) CURRENT TECHNOLOGIES

In the realm of current IoT technologies, several challenges persist despite advancements. The proliferation of IoT devices has resulted in a significant increase in data volume, necessitating more robust data processing and storage solutions [198]. Energy efficiency continues to be a critical issue, particularly for battery-operated devices. The diversity of devices and communication protocols creates interoperability problems [199], [200], and ensuring data security and privacy in resource-constrained devices remains challenging.

To address these challenges, advanced MCUs with higher processing power and integrated hardware accelerators [201] for specific tasks are being utilized. Edge computing is employed to shift data processing tasks to the edge, reducing data transmission requirements and lowering latency [202].

D. FUTURE DIRECTIONS

Future directions in MTC devices include the use of TinyML to enhance data processing, to achieve significant energy reduction by processing semantic queries locally [187]. Quantum computing is being explored for its potential to boost accuracy and speed, for improvements in data classification accuracy using quantum neural networks [188], [189]. AI accelerators and neuromorphic processors are being developed to handle ML tasks efficiently, with innovations like RF neuromorphic sensors and NeuroRadar offering low-power, high-performance solutions for IoT [190], [191]. Additionally, advancements in memory devices and data compression techniques, such as hybrid storage architectures [183], [184] and TinyML-based compression, are optimizing energy consumption and data management in resource-constrained environments [185].

E. CASE STUDY: RRAM IN SMART HOMES

The work in [203], [204], [205] showcases the use of RRAM-based AI models to enhance the management and optimization of home functions such as lighting, heating, and security. The integration of AI improves control, reliability, and automation within smart home systems while the low power consumption of RRAM contributes to more sustainable and eco-friendly smart homes. Its high-speed data processing capabilities enable real-time responses to user commands and environmental changes, enhancing the overall functionality and responsiveness of smart home systems. AI models powered by RRAM learn from user behaviours and preferences, offering personalized control over home systems, and AI-driven security systems using RRAM can swiftly process and respond to potential security threats, thereby enhancing home safety.

V. SENSING SUBSYSTEM

A. OVERVIEW

The energy usage within a node's sensing subsystem pertains to the quantity of electrical energy that the sensors and related components consume while carrying out tasks related to data sensing and acquisition. The sensing subsystem's role involves capturing and transforming physical or environmental phenomena into electrical signals that the node can subsequently process.

Below is an overview of the typical elements found within the sensing subsystem:

1) *Physical Sensors:* These serve as the core elements of the sensing subsystem and encompass various sensor types, including temperature sensors, pressure sensors [206], humidity sensors [207], light sensors [208], [209], motion sensors [210], [211], gas sensors, and more. Each sensor is designed with a purpose of measuring a specific physical quantity and converting it into an electrical signal.
2) *ADC:* This is a critical part of a sensor node tasked for converting analog signals from sensors into digital data, which can be processed by the node's digital systems. The ADC takes continuous analog voltage or current output from the sensor and converts it into digital values, usually represented as binary numbers.
3) *Sensor Interfaces:* The sensing subsystem also comprises interfaces that establish connections between the physical sensors and the remaining electronic components of the sensor node. These interfaces can be either analog or digital, depending on the sensor types in use. They facilitate the necessary connections for signal transmission, power supply, and control between the sensors and the computational subsystem of the sensor node.

Energy consumption within this subsystem is expressed as [157]:

$$E_s = L(S_i) \times V_{dc} \times I(S_i) \times T(S_i) \tag{2}$$

where, S_i represents the energy consumption associated with sensing. $I(S_i)$ signifies the required current. $T(S_i)$ denotes the duration required for detection and data collection.

The literature following pertains to various techniques and algorithms related to sensing subsystems in wireless sensor nodes and is summarised Table 12. These techniques and algorithms are designed to enhance the efficiency, accuracy, and energy usage of sensing activities in WSNs. They address challenges such as optimizing sensor coverage, reducing redundancy, managing energy consumption, enhancing data accuracy, and extending the lifespan of battery-powered sensor nodes.

B. TRENDS

WSNs encounter the challenge of efficiently monitoring targets while prolonging the network's operational lifespan. In the work presented in [212], they introduce the Adaptive Sensor Sensing Range (ASSR) technique as a solution to this challenge. ASSR optimizes the sensing range of each sensor to ensure comprehensive target coverage while minimizing redundancy. Experimental findings indicate that ASSR enhances network longevity by 20% in small networks and 8% in larger networks compared to recent methods. In the context of WSNs, the concern of imbalanced energy usage is addressed in [213] through the proposal of an adaptive sensor scheduling algorithm designed for energy-efficient target monitoring. This algorithm selects tasking nodes based on a decision function, achieving a balance in local energy consumption and optimizing sensor scheduling. It also improves tracking accuracy by incorporating a particle filter algorithm. Simulated results demonstrate significant enhancements in tracking accuracy, along with a 41.67% reduction in energy consumption compared to previous methodologies.

To cater to the requirements of IoT applications for the long term, which need to maintain accuracy in data and time while extending the lifespan of devices powered by batteries with energy-intensive transmitting modules, [214] introduces an adaptive sensing algorithm. This algorithm leverages techniques such as Send-on-Delta and Grey Model first-order prediction, a dynamic time window, and eliminating outliers. Numerical outcomes underscore the advantages of this algorithm over a linear approximation, emphasizing its effectiveness in terms of flexibility, precision, and data transfer minimization. This algorithm proves particularly valuable for applications with extended sensing periods and high sampling rates, delivering noteworthy performance enhancements. In the realm of energy-efficient data gathering, [215] proposes a mechanism that employs compressed sensing algorithms. This mechanism utilizes a cloud-based data prediction model to forecast sensory data, focusing on data categories or ranges rather than precise values.

IoT nodes only transmit their data to the cloud when there is a category mismatch. Experimental assessments confirm the superiority of this approach over existing techniques concerning network traffic and energy consumption. Traditional techniques for conserving energy in WSN have limitations, particularly in scenarios where sensors expend more energy than communication. To address this, [216] presents a dynamic sampling algorithm that calculates the most efficient sampling frequencies for sensors in real-time. This algorithm is designed to efficiently manage energy consumption for both sensors and radio while maintaining high data accuracy. Simulation experiments, using a snow-monitoring sensor as a case study, demonstrate that the adaptive algorithm is capable of reducing the quantity of acquired samples by up to 79% compared to a fixed-rate approach, while performing similarly to a constant-rate scheme with known sampling frequencies in advance. Furthermore, in the context of monitoring applications, [217] investigates the power consumption of sensing subsystems and implements a power gating technique to reduce energy consumption. This technique selectively activates sensor elements, thereby achieving energy savings.

C. CHALLENGES AND SOLUTIONS

1) EARLY TECHNOLOGIES

Early IoT technologies faced several challenges related to sensing capabilities. One significant challenge was the need for real-time processing of data. Immediate analysis was crucial to ensure timely responses and effective decision-making. The solution to this challenge was the implementation of Real-Time Operating Systems (RTOS) [229]. RTOS facilitated the prompt processing of data, ensuring that systems could operate efficiently and respond in a timely manner.

Additionally, sensors were prone to drift and degradation over time, which could impact their accuracy. Environmental factors such as temperature fluctuations or mechanical wear could exacerbate this issue. To counteract these effects, automated calibration systems were introduced [230]. These systems involved self-calibrating sensors that periodically adjusted their measurements to maintain accuracy [221]. This automated approach helped to ensure that sensors remained reliable and accurate over extended periods, mitigating the impact of environmental changes and usage wear.

2) CURRENT TECHNOLOGIES

Current IoT technologies face significant challenges in data acquisition and sensor selection. Efficiently managing and processing large volumes of sensor data necessitates robust systems capable of high data throughput and integrity, leveraging edge computing and ML for real-time analysis and energy-efficient design. Research such as [220] explores lightweight ML models for indoor environmental quality estimation using low-cost edge architectures, focusing on efficient data processing at the source. Meanwhile, [202] surveys advances in deploying ML on low-resource edge devices and cloud networks, addressing challenges like data security and resource management. Additionally, selecting appropriate sensors for specific applications is complex, requiring comprehensive evaluation methods and standardized criteria to ensure that sensors effectively meet application needs [218], [219].

D. FUTURE DIRECTIONS

Future directions in sensing technology address key challenges related to sensing capabilities, lifespan, sensitivity, and autonomous operation. Early sensors had limited accuracy, which was improved through basic sensor fusion. Recent advancements leverage AI to enhance data analysis and decision-making, addressing static configurations and promoting energy efficiency in WSNs. Studies highlight the integration of AI in improving sensor performance and energy practices [225], [226]. Additionally, novel materials, such as nanomaterials [223] and cellulose nanocrystals (CNCs) [224], are being developed to enhance sensor durability, sensitivity, and accuracy. Challenges related to calibration and autonomous operation are also being addressed with automated systems and smart power management techniques, including mechanical energy harvesting technologies to support self-powered sensors [227], [228] and online calibration methods [221], [222].

E. CASE STUDY: PREDICTIVE MAINTENANCE IN A MANUFACTURING PLANT

The study in [231] tackles the critical issue of identifying undesirable events in industrial machinery, which are

TABLE 12. Technology analysis [212], [213], [214], [215], [216], [217], [218], [219], [220], [221], [222], [223], [224], [225], [226], [227], [228].

Technique	Technologies	Advantages	Challenges
Adaptive Sensing and Scheduling	Adaptive Sensor Sensing Range (ASSR), Adaptive Sensor Scheduling Algorithm, Adaptive Sensing Algorithm	Optimizes sensor coverage and scheduling, balances energy consumption, enhances tracking accuracy	Complexity in implementation, potential computational overhead
Data Compression and Prediction	Compressed Sensing Algorithms, Cloud-based Data Prediction Models	Reduces network traffic and energy consumption , focuses on data categories for efficient transmission	May require significant computational resources in the cloud
Dynamic Sampling and Power Management	Dynamic Sampling Algorithm, Power Gating Technique	Efficiently manages energy consumption (up to 40% savings), reduces sampling frequency without sacrificing data accuracy	Implementation complexity, potential impact on sensor responsiveness
Edge Computing and ML	Edge Computing, ML Algorithms for Real-time Data Analysis	Enables real-time data processing, reduces latency (30% improvement) and improves data accuracy	Higher initial setup costs, demands advanced computational techniques
Advanced Materials and Self-Powered Sensors	Advanced Sensor Materials, Self-Powered Sensors	Enhances sensor durability and sensitivity, enables independent sensor operation without external power	High development and material costs, limited by current technology advancements

often poorly represented in historical data. The researchers developed an innovative predictive maintenance method that significantly reduces false positive alarms. This method employs outlier detection techniques and eXplainable AI (XAI) to analyze data collected from wireless sensors monitoring vibration and temperature. The system adapts to the data, interacts with dispatchers, and uses XAI to enhance the interpretability of the results. This approach ensures that the predictive maintenance system can function effectively even with limited historical failure data, preventing the generation of excessive false alarms that could overwhelm operators.

The system's ability to predict failures accurately and reduce false alarms contributes to improved operational efficiency. Maintenance activities can be better planned and executed. By optimizing maintenance schedules and reducing unnecessary maintenance actions, the system indirectly contributes to improved energy efficiency. Additionally, well-maintained equipment operates more efficiently, consuming less energy and resources.

VI. RF SUBSYSTEM

A. OVERVIEW

Enhancing the radio subsystem within a node entails the application of various methods and considerations aimed at boosting its performance, power efficiency, and reliability. The energy expended by the radio can be represented as [157]:

$$E_t = \begin{cases} L(S_i) \times E_{elec} + L(S_i) \times E_{fs} \times d^2, & \text{when } d < d_0 \\ L(S_i) \times E_{elec} + L(S_i) \times E_{mp} \times d^4, & \text{when } d > d_0 \end{cases} \quad (3)$$

where the energy consumption for transmitting or receiving a single bit of information is represented by E_{elec}. The values of E_{fs} and E_{mp} are determined by the characteristics of the transmitter amplifier, with E_{fs} pertaining to the free space propagation model and E_{mp} corresponding to the multipath model. Additionally, the variables d and d_0 denote the separation between the transmitter and receiver and a predefined threshold distance, respectively. To reduce energy usage in wireless communication, various radio parameters such as antenna orientation, cognitive radio, and modulation schemes can be optimized. Research has indicated that the radio module is the primary contributor to battery depletion in a node. Consequently, certain literature has placed emphasis on radio optimization, as demonstrated in [32].

B. TRENDS

1) DIRECTIONAL ANTENNAS

This category of antennas possesses the capability to transmit and receive signals in a single direction. Directional antenna technologies such as patch, Yagi-Uda, horn, parabolic reflector, phased array, microstrip, log-periodic, and helical antennas are used to enhance communication range and focus. These antennas offer various advantages like high gain, directivity, and beam steering, suitable for diverse MTC applications requiring efficient and targeted signal transmission. The utility of directional antennas in the development of new media access control (MAC) protocols is discussed in [232]. In [38], a cooperative communication scheme is presented, which generates a simulated transmitter using multiple antennas by combining several single-antenna devices. The advantages of employing directional antennas are elaborated upon in [233], encompassing reduced interference, enhanced spatial reuse, improved network capacity, and an extended transmission range. In [234], the challenge of localizing MTC nodes in indoor environments is addressed. The authors introduce a method called the

Reliable Data Collection Mechanism, which employs six antennas to attain an omni-directional radiation pattern for localization and data collection, while taking into account the energy left in the node. In the research conducted by [235], the use of directional antennas in WSNs for large food grain storage is investigated. The study demonstrates that directional antennas offer greater energy efficiency compared to omnidirectional antennas in wireless communication.

2) MODULATION OPTIMIZATION

The objective of modulation optimization is to reduce energy usage by fine-tuning modulation parameters. Various modulation technologies like AM, FM, PM, QAM, FSK, PSK, MSK, OFDM, LoRa, and GFSK are employed, each offering unique benefits in terms of data rate, power consumption, range, and noise immunity. These technologies enable tailored communication solutions for diverse IoT applications, balancing efficiency and performance based on specific requirements. Studies have demonstrated the significance of striking the right balance among factors like constellation size, node separation, and data rate. Emphasizing the importance of meeting QoS criteria for throughput and latency to minimize energy consumption in battery-operated MTDs, the authors in [236] underscore this aspect. Meanwhile, in the pursuit of identifying the most efficient transmission method, the research in [237] compares three digital modulation techniques, specifically MQAM, MPSK, and MFSK, to determine the most energy-efficient approach. Similarly, the optimal modulation strategy is explored in [238], with a focus on digital modulation schemes like MQAM, MPSK, MFSK, and MSK, which are demonstrated to achieve the most favorable energy usage in MTC scenarios. To substantially extend battery life, the article presented in [239] assesses the energy efficiency of the modulation schemes below:

1) *Amplitude Shift Keying (ASK)*
2) *Binary Phase Shift Keying (BPSK)*
3) *Offset Quadrature Phase Shift Keying (OQPSK)*

Furthermore, the authors aim to identify the transmission scheme that offers the most efficient energy consumption for a specific number of transmitted bits. According to their findings, optimizing modulation parameters and transmission duration can result in energy savings of up to 60% for the transmission of uncoded data.

3) TRANSMISSION POWER CONTROL (TPC)

Another method to improve energy efficiency involves the adjustment of radio transmission power. TPC technologies in the RF subsystem of include adaptive power control, closed and open-loop power control, ML-based strategies, and EH-aware approaches, all aimed at optimizing power consumption and maintaining reliable communication. These technologies also encompass interference management, cognitive radio-based power control, and cooperative communication techniques to enhance energy efficiency and network performance. The authors of [240] take into account the unequal energy consumption patterns of MTDs as they propose an algorithm to modify the transmission power of these devices. Addressing the challenge of maintaining low-power consumption and minimizing interference in WSNs, which fall under the category of MTC networks, is the focal point of analysis in [241]. This study aims to strike a balance between the standard of communication and power usage by introducing adaptive data rate based on fuzzy logic approach for TPC. Furthermore, the regulation of transmission power level for sensors is also implemented in Wireless Body Area Networks (WBANs). This approach takes various factors into consideration, including the distance to the destination, link quality, and other relevant criteria, as outlined in [242].

4) COGNITIVE RADIO (CR)

This technology enables an intelligent radio system to dynamically identify and locate accessible communication channels. CR technologies such as dynamic spectrum access (DSA), spectrum sensing, and adaptive modulation and coding (AMC) enhance spectrum efficiency and reduce interference. Additionally, advanced techniques like ML for spectrum decision-making and software-defined radio (SDR) provide flexibility and adaptability, ensuring optimal spectrum utilization and improved network performance.

CR involves substantial energy consumption primarily due to the utilization of SDR, which allows transceivers to automatically adjust their communication parameters in response to network conditions, as described in [243]. The research presented in [244] aims to develop energy-efficient cognitive radio networks that can intelligently manage battery energy resources. In this work, the authors introduce a constrained optimization problem with a non-linear fractional programming objective, which is designed to determine the power allocation necessary for maximizing energy efficiency. In the context of sensor networks employing cognitive radio technology, [245] introduces a hybrid sensing method that relies on a collaborative approach. On the other hand, [246] concentrates on the utilization of an energy detection technique when proposing a cooperative spectrum sensing system. This system is employed to detect available channels and optimize energy utilization.

5) SLEEP SCHEDULING

Sleep scheduling technologies like duty cycling, wake-up radios (WuR)s, adaptive listening, low power listening, synchronized sleep schedules, on-demand wake-up, dynamic sleep interval adjustment, and asynchronous wake-up schemes are crucial for reducing power consumption. These techniques minimize the active time of the RF subsystem by efficiently managing its sleep and wake-up cycles, balancing energy efficiency with communication needs. In their work [247], an energy-efficient sleep scheduling mechanism is proposed, which intelligently schedules MTDs into either sleep or active modes. This mechanism has been proven to be both energy-efficient and beneficial in enhancing data accuracy. In the context of WSNs, [248] strives to optimize energy efficiency by introducing an adaptive sensing scheduling strategy that has demonstrated superior performance compared to various existing strategies. Conversely, [249] suggests a TDMA-based scheduling scheme that promotes energy conservation by scheduling wakeup intervals to minimize energy usage.

To address energy consumption challenges in MTC, a common approach involves duty cycling, where nodes periodically enter sleep mode to conserve energy. However, scheduled duty-cycling presents a trade-off between energy usage and data delivery delay. To mitigate this trade-off, an additional WuR channel is introduced, enabling nodes to quickly awaken for data transmission, as detailed in [250]. This paper introduces power usage models for various duty cycling techniques and compares the performance of the WuR approach with planned duty cycling methods. The goal is to determine the optimal WuR energy consumption that makes it a viable alternative in typical IoT networks. Through this evaluation, the paper seeks to assess the competitiveness of the WuR approach in reducing energy consumption and minimizing data delivery delay in IoT networks.

6) CHANNEL CODING

Channel coding technologies such as convolutional codes, turbo codes, low-density parity-check (LDPC) Codes, Reed-Solomon Codes, polar codes, BCH Codes, and Hamming Codes play crucial roles in ensuring reliable data transmission by providing robust error detection and correction capabilities. In [251], the primary focus lies in examining the energy efficiency of polar codes and LDPC codes, and conducting a comparative analysis of these two Forward Error Correction (FEC) techniques in the context of IoT networks. On the other hand, in [252], the paper examines the evaluation of energy efficiency across three distinct types of hybrid automatic repeat request (HARQ) strategies:

1) *Type I HARQ*
2) *HARQ with chase combining (HARQ-CC)*
3) *HARQ with incremental redundancy (HARQ-IR)*

These studies aim to elucidate the energy efficiency characteristics and performance of the respective coding and HARQ techniques within their specified domains.

7) BEAMFORMING

Beamforming is a signal processing method employed in wireless communication systems, particularly in RF and microwave systems, to focus the transmission or reception of electromagnetic signals in a specific direction. The principal objective of beamforming is to enhance the performance of a communication link by directing the signal energy towards the intended receiver or target, while simultaneously reducing interference from other directions [253]. Key beamforming technologies include digital, analog, and hybrid beamforming, with applications ranging from fixed and adaptive beamforming to massive MIMO and millimetre-wave communications. Emerging techniques like ML-based beamforming enhance adaptability and performance in dynamic environments, while specific applications such as vehicular and satellite beamforming ensure reliable communication in specialized contexts.

To evaluate the energy efficiency of different beamforming strategies, the authors in [254] simulate a single-cell wireless system with varying numbers of base station (BS) antennas and user equipment (UEs). The simulation considers three beamforming techniques;

1) *Maximum Ratio (MR) Beamforming:* This approach amplifies the signal from a user with a weight proportional to the signal strength. It is computationally simple but can be less efficient with interference.
2) *Regularized Zero Forcing (RZF) Beamforming:* This technique reduces interference by nullifying signals in unwanted directions, providing a balanced approach to performance and complexity.
3) *Minimum Mean Square Error (MMSE) Beamforming:* A more advanced method that minimizes the error between transmitted and received signals, often offering higher spectral efficiency at the cost of increased computation.

The 3D plots in Fig. 6, 7, and 8 illustrate the energy efficiency across different configurations of BS antennas (M) and UEs (K) for MR, RZF, and MMSE beamforming. These plots reveal the optimal configurations for each technique, highlighting the number of UEs and BS antennas that yield the maximum energy efficiency. In the plots, a clear trend emerges; as the number of BS antennas increases, the energy efficiency typically improves, but there is an optimal point beyond which additional antennas provide diminishing returns. This phenomenon is due to increased power consumption from additional processing and hardware. Among the three techniques, MMSE tends to offer the highest energy efficiency due to its ability to handle interference more effectively. However, it is computationally more complex than MR and RZF. RZF provides a balance between performance and computational complexity, while MR is the simplest but less efficient in high-interference scenarios.

In the study presented in [255], two strategies are introduced to reduce power consumption in communication systems: hybrid beamforming and low-resolution ADCs in digital beamforming. The paper emphasizes the importance of harnessing the millimeter wave spectrum in 5G networks while addressing power challenges in the analog front-end of receivers with multiple antennas. In [256], energy efficiency is mentioned as one of the factors considered when simulating 5G networks with beamforming capabilities. The paper compares various beamforming architectures with a 4G reference network. Similarly, [257] explores the design of energy-efficient fully analog precoders and combiners in millimeter-wave short-packet communication scenarios.

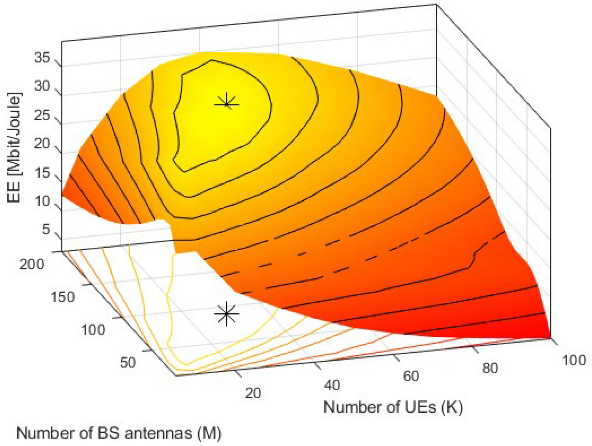

FIGURE 6. Energy efficiency with Regularized Zero Forcing (RZF) Beamforming.

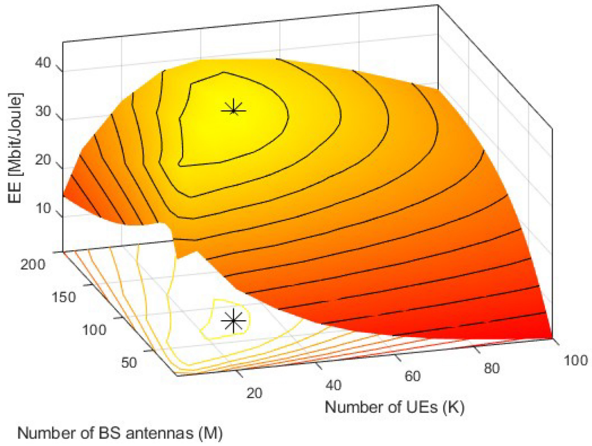

FIGURE 7. Energy efficiency with Minimum Mean Square Error (MMSE) Beamforming.

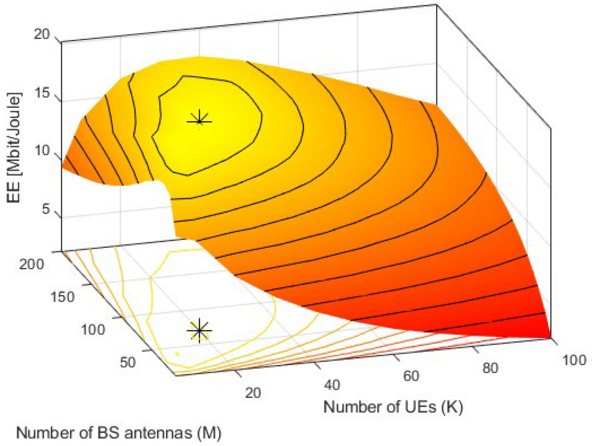

FIGURE 8. Energy Efficiency (EE) with Maximum Ratio (MR) Beamforming.

In [258], the focus is on designing and optimizing beamforming techniques, power allocation, and interference management in an energy-efficient cooperative NOMA system with multi-antenna ambient backscatter communication assistance. The paper optimizes physical layer parameters to enhance energy efficiency. The integration of reconfigurable intelligent surfaces (RIS) or meta-surfaces with cell-free (CF) networks to enhance both spectral and energy efficiency is examined in [259]. Conversely, [260] concentrates on optimizing beam switching to enhance communication performance and reduce energy wastage. In [261], the proposed scheme aims to reduce uplink transmission power in an IoT network assisted by RIS, focusing on energy efficiency at the physical layer. The optimization of analog beamforming in massive MIMO systems to achieve high performance while minimizing energy consumption is addressed by [262]. The paper combines phase shifters that are adjustable and phase shifters that maintain a constant phase in the architecture to efficiently shape transmitted signals and improve energy efficiency. In [263], the study focuses on jointly optimizing beamforming, RIS phase shift, and EH to maximize energy efficiency in a multiple-input single-output (MISO) downlink system. The goal is to leverage RIS technology to improve energy efficiency while maintaining spectral efficiency. The work in [264] optimizes the energy efficiency of a hybrid pre-encoding design with quantization, introducing alternating minimization algorithms to enhance completely and partially connected structures for improved energy savings. In [265], challenges associated with directional antennas, such as signal interference and antenna adjustments, are highlighted. Meanwhile, [266] discusses the complexities of comparing Time Division Multiple Access (TDMA) and NOMA strategies in uplink MTC with EH due to non-convex optimization problems and heterogenous MTDs. Managing the increasing transistor count on a singular chip for power optimization is a challenging task, as discussed in [267]. Additionally, [268] addresses challenges in synchronizing nodes in communication systems that use directional antennas, where high gains are achieved but unsynchronized nodes face prolonged synchronization due to narrow beams. The paper also mentions the high cost of digital phased array antennas as a limitation.

8) ENERGY-EFFICIENT COMMUNICATION PROTOCOLS

Energy-efficient communication protocols play a crucial role in enabling efficient and reliable communication in MTC. These technologies summarised in Table 13 and compared in Table 14 are essential for managing the wireless transmission of data between devices, especially in MTC applications and include Low Power Wide Area Networks (LPWAN) technologies [273], [274], [275] like Long Range Wide Area Network (LoRaWAN), Sigfox, Narrowband IoT (NB-IoT) and MAC Protocols like TDMA [276], [277], Carrier Sense Multiple Access (CSMA) protocol [278]. Other technologies include IEEE 802.11ah [279], [280], [281], and BLE.

9) LPWAN TECHNOLOGIES

1) LoRaWAN: Advancements and methodologies for optimizing power consumption in MTC applications using

TABLE 13. Overview of LoRaWAN, Sigfox, 802.11ah, NB-IoT, and BLE [50], [269], [270], [271], [272].

Parameter	**LoRaWAN**	**Sigfox**	**802.11ah (WiFi HaLow)**	**NB-IoT**	**BLE**
Range	Up to 15km	Up to 50km	Up to 1km	Up to 35km	Up to 100m
Data Rate	0.3 kbps to 50 kbps	100 bps to 600 bps	150 kbps to 347 Mbps	20 kbps to 250 kbps	Up to 2 Mbps
Power Consumption	Very low	Very low	Moderate to low	Low	Very low
Frequency Band	868/915 MHz	868/915 MHz	Sub-1 GHz (900 MHz)	LTE frequency bands	2.4 GHz
Modulation	LoRa (CSS)	BPSK	OFDM	QPSK	GFSK
Bandwidth	125 kHz to 500 kHz	100 Hz	1 MHz to 16 MHz	180 kHz	2 MHz
Maximum Messages/Day	Unlimited	140(UL),4(DL)	Unlimited	Unlimited	Unlimited
Standardization	LoRa Alliance	ETSI	IEEE 802.11ah	3GPP	Bluetooth SIG
Application Examples	Smart Cities, Environmental Monitoring	Asset Tracking, Industrial IoT	IoT, Smart Agriculture, Smart Metering	Smart Cities, Industrial IoT	Wearables, Health Monitoring

LoRaWAN have been discussed in numerous works of literature. An energy efficient LoRa (EE-LoRa) algorithm is proposed in [282] to enhance the energy efficiency of LoRaWAN networks by optimizing spreading factor selection and power control, significantly improving energy efficiency compared to legacy systems. In [283] the study explores energy efficiency optimization for subterranean LoRaWAN networks, using reinforcement learning to manage transmission configurations, demonstrating substantial energy savings. The work in [73] provides insights into the design of energy efficient MTC devices using LoRaWAN technology, focusing on strategies to extend battery life, while [284] explores the limitations and capabilities of LoRaWAN, providing insights into its performance in terms of energy efficiency and communication range.

2) Sigfox: Sigfox [285], an LPWAN technology [286], plays a significant role in MTC by offering extensive coverage and low energy consumption, making it ideal for IoT applications. By leveraging Sigfox's energy-efficient protocol, MTC can achieve prolonged battery life and operational efficiency, crucial for sustainable IoT deployments. In [287], the study focuses on improving the efficiency of Sigfox networks by reducing collisions and energy consumption through a new slot- and channel-allocation protocol, enhancing the overall performance and scalability of MTC applications. The energy consumption challenges associated with over-the-air firmware updates in Sigfox and compares it with other LPWAN technologies are addressed in [288]. The analysis highlights the substantial energy required for full firmware updates in Sigfox and emphasizes the efficiency of partial updates, thereby contributing to discussions on energy efficiency in IoT networks using Sigfox.

3) Narrowband IoT (NB-IoT): NB-IoT is a specialized LPWAN technology with low power consumption, enhanced indoor coverage, and the ability to connect a massive number of devices efficiently. By optimizing resource allocation and implementing energy-efficient techniques, NB-IoT significantly reduces the energy consumption and carbon footprint of MTC applications, promoting sustainable and green IoT deployments. Reference [289] examines NB-IoT, and its advantages in reducing energy consumption of IoT devices, thereby promoting green communication. It also proposes a green NB-IoT model for smart agriculture to further enhance energy efficiency in IoT applications. The study in [290] addresses the high energy consumption and carbon footprint issues associated with the growing number of IoT devices and discusses the role of NB-IoT. The abstract highlights NB-IoT's technical features, resource allocation, and energy efficiency techniques, proposing two novel methods, zonal thermal pattern analysis (ZTPA) and energy efficient adaptive health monitoring system (E2AHMS), to promote Green IoT and enhance energy efficiency.

10) IEEE 802.11AH (WI-FI HALOW) & BLE

The authors in [291] provide an in-depth analysis of IEEE 802.11ah, focusing on its key features and capabilities to support MTC applications, highlighting its energy efficiency and long-range communication benefits. New MAC protocols in IEEE 802.11ah that enhance energy efficiency and optimize throughput, particularly suitable for IoT networks are explored in [292]. The research in [271] studies the energy consumption and data throughput for various BLE versions, providing insights into how different connection parameters affect energy efficiency in MTC applications. In [293], a connection-less communication scheme for BLE that improves communication and energy efficiency in MTC applications with many devices is proposed and the work in [294] evaluates the performance of IPv6-oriented BLE mesh networks, focusing on latency, round trip time, and energy consumption, highlighting BLE's suitability for MTC mesh networking.

C. MAC PROTOCOLS

MAC protocols are essential for managing access to the communication medium in wireless networks. They determine how multiple devices share the same communication channel without interference, ensuring efficient and reliable data transmission. Energy-efficient MAC protocols are particularly important in MTC as they help reduce power consumption and extend the battery life of devices.

1) TIME DIVISION MULTIPLE ACCESS (TDMA) PROTOCOLS

Several works of literature provide insights into the implementation and benefits of TDMA-based protocols in MTC networks, highlighting their role in enhancing energy efficiency and optimizing communication in dense network environments. An overview of energy-efficient MAC protocols, including TDMA, in the context of underwater WSNs (UWSNs) is provided in [295] which discusses the energy-saving mechanisms of these protocols and their applicability to MTC. The survey in [296] highlights the importance of energy-efficient communication protocols in MTC, including TDMA, and their role in maximizing network lifetime and reducing power consumption. The development of a TDMA-based access protocol designed to improve energy efficiency and manage dense networks with moving nodes in MTC applications is discussed in [276].

2) CARRIER SENSE MULTIPLE ACCESS (CSMA) PROTOCOLS

The implementation and benefits of CSMA-based protocols in MTC networks, highlighting their role in enhancing energy efficiency in various network environments have been studied. New CSMA-based MAC protocols that allow nodes to enter sleep mode, combining throughput optimality with energy efficiency are studied in [292]. The survey [295] provides an overview of energy-efficient MAC protocols, including CSMA, in the context of underwater WSNs and their applicability to MTC and in [297] the work presents a cross-layer design approach to improve energy efficiency and reliability in WSNs using CSMA-based protocols.

3) FREQUENCY DIVISION MULTIPLE ACCESS (FDMA)

In [298] single carrier-frequency division multiple access (SC-FDMA) with index modulation for uplink transmissions in MTC applications, focusing on maximizing energy efficiency is explored. The contribution in [299] compares Time Slotted Channel Hopping (TSCH), which combines TDMA and FDMA, in industrial MTC networks to enhance energy efficiency and communication reliability while in [300] the study investigates resource allocation strategies in intelligent reflecting surface (IRS)-assisted wireless-powered FDMA MTC networks, focusing on energy efficiency.

4) CODE DIVISION MULTIPLE ACCESS (CDMA)

The research conducted in [301] examines the use of CDMA in conjunction with UAVs to improve energy efficiency in MTC networks, proposing optimization algorithms for better energy management. The authors of [302] analyze the application of CDMA with beamforming techniques to enhance energy efficiency in MTC networks, demonstrating significant improvements in system performance while the investigation in [303] the use of RIS with CDMA to improve energy efficiency and signal quality in MTC applications.

D. CHALLENGES AND SOLUTIONS

1) EARLY TECHNOLOGIES

Early RF subsystems were hindered by the lack of integration among transmission, reception, and signal processing components, leading to bulky designs and high power consumption that limited battery life in sensor nodes [304]. This inefficiency resulted in lower sensitivity and selectivity, affecting communication range and reliability [305], while limited frequency bands caused congestion and interference issues [306]. Solutions to these problems included integrating RF components into fewer chips, which improved space efficiency and power consumption [307], [308], and the adoption of basic signal processing techniques that enhanced signal quality and reduced noise [309].

2) CURRENT TECHNOLOGIES

Despite technological advancements, current RF subsystems grapple with challenges such as miniaturization and power efficiency [42]. Reducing size while preserving performance is difficult, and power efficiency is crucial, especially for battery-operated devices where RF communication can significantly drain battery life. A solution is to include System-on-Chip (SoC) designs for reducing size and power [310], [311].

Energy-efficient communication protocols like BLE and Zigbee, along with optimized RF circuitry, can extend battery life. The surge in wireless devices has intensified interference and spectrum congestion, complicating interference management [312]. Advanced techniques like OFDM and LDPC coding can mitigate interference and enhance communication reliability and data rates [313] as well as advanced filtering and digital signal processing (DSP).

E. FUTURE DIRECTIONS

The future of network technology faces substantial challenges in maintaining energy efficiency [314] and sustainability as demands for high data rates escalate, driven by emerging applications such as augmented reality, autonomous vehicles, and extensive IoT deployments [315], [316]. To meet these demands, innovative solutions are essential. Technological advances such as massive MIMO [18], millimeter-wave (mmWave) and terahertz (THz) communication systems are on the rise [317], [318]. Integrating intelligent reflecting surfaces (IRSs) with massive MIMO [319] can significantly enhance signal quality and coverage while reducing energy consumption. Furthermore, achieving higher energy efficiency in 6G networks involves

TABLE 14. Technology analysis [273], [274], [275], [286].

Protocol	Power Subsystem	Processing Subsystem	Sensing Subsystem	RF Subsystem
LoRaWAN	Low power consumption, often powered by batteries or solar cells. Typical battery life of 10+ years in low-duty cycle applications.	Low-power microcontrollers (e.g., ARM Cortex-M), optimized for energy efficiency. Processing speed of 48 MHz	Basic sensors for environmental monitoring (e.g., temperature ±1°C, humidity ±3%). Response time of 100 ms for data acquisition.	Long-range transceivers operating in the unlicensed ISM bands,up to 15 km range, data rates from 0.3 to 50 kbps, with adaptive data rate and sleep modes.
Sigfox	Very low power consumption, typically powered by batteries with long lifespans. Battery life up to 10 years in low-duty cycle applications.	Ultra-low-power microcontrollers (e.g., STM32), designed for simple data processing.	Simple, low-power sensors (e.g., GPS for asset tracking, basic environmental sensors). GPS accuracy of ±50 meters	Ultra-narrowband transceivers, optimized for long-range (up to 50 km), low-data-rate (100 bps to 1 kbps) communication.
NB-IoT	Moderate power consumption, can be powered by batteries or mains in fixed installations. Typical battery life of 10 years in low-duty cycle applications.	More powerful microcontrollers (e.g., ARM Cortex-M, Cortex-A), capable of handling higher data rates (up to 250 kbps) and complex tasks.	Advanced sensors for industrial and smart metering applications (e.g., gas, water, electricity meters).	Cellular transceivers operating in licensed LTE bands, supporting low power wide area networks with reliable coverage. Data rates from 10 to 100 kbps.
BLE	Low power consumption, designed for devices with small batteries. Battery life up to 10 years in active use.	Low-power microcontrollers with integrated BLE support (e.g., Nordic nRF52). Processing speed of 64 MHz	Various sensors for wearable and smart home applications (e.g., accelerometers, heart rate monitors). Response time of 50 ms for sensor data.	Short-range BLE transceivers, optimized for high data rates (up to 2 Mbps) with adaptive frequency hopping and low power modes.
IEEE 802.11ah	Moderate to low power consumption, suitable for battery or mains-powered devices. Battery life up to 5-10 years in low-duty cycle applications.	Efficient microcontrollers that can handle moderate data rates (up to 1 Mbps) and complex tasks (e.g., ARM Cortex series).	Sensors for smart city, smart agriculture, and industrial applications e.g., environmental sensors, smart meters).	Long-range transceivers operating in the sub-1 GHz bands, up to 1 km range, data rates from 100 kbps to 1 Mbps, with features like Target Wake Time (TWT) and Restricted Access Window (RAW).

leveraging AI and ML [320] for predictive algorithms to optimize transmission power [321] and duty cycles [322]. As technology progresses, addressing sustainability and minimizing the carbon footprint of network infrastructures become increasingly important [323]. Employing new materials, such as graphene and advanced semiconductors [324], as well as technologies like 3D integration, plays a vital role in managing high frequencies and improving overall performance.

F. CASE STUDIES

1) COGNITIVE RADIO FOR SMART CITY SPECTRUM MANAGEMENT

This case study [325] explores the application of CR technology for spectrum management in smart cities. The study focuses on utilizing CR to dynamically allocate and manage spectrum resources among various smart city applications, such as traffic monitoring, public safety communications, and environmental sensing. CR dynamically identifies and exploits spectral holes, improving the overall utilization of available spectrum and reducing congestion in high-demand areas. It reduces energy consumption by allowing devices to operate on less congested frequencies, leading to lower transmission power requirements and extended battery life. CR also enhances the performance of smart city applications, such as real-time traffic monitoring and emergency response systems, by providing robust and reliable communication channels while also ensuring continuous and reliable connectivity for critical smart city applications by minimizing interference and optimizing channel selection.

2) ENERGY-EFFICIENT SLEEP SCHEDULING FOR PRECISION AGRICULTURE

The case study in [326], [327] explores the implementation of sleep scheduling strategies in WSNs used in precision agriculture. The focus is on optimizing the power consumption of sensor nodes by incorporating sleep scheduling algorithms that allow sensors to enter low-power states when not actively transmitting data. This approach is applied to soil moisture and temperature monitoring systems in crop fields, where sensors periodically wake up to collect and transmit data, then return to a sleep state to conserve energy.

The active time of sensor nodes is reduced by sleep scheduling and the overall energy consumption is significantly decreased, extending the battery life of sensors and reducing maintenance costs. Reliable and energy-efficient monitoring allows farmers to make informed decisions about irrigation, fertilization, and other crop management practices, leading to improved crop yields and resource conservation.

3) SMART AGRICULTURE USING LORAWAN

The case study [328], [329], [330] focuses on the implementation of LoRaWAN technology in smart agriculture, specifically for monitoring and managing irrigation in vineyards. The system integrates various soil, plant and environmental sensors connected through LoRaWAN for data transmission. The sensors collect real-time data on soil moisture, temperature, and humidity, which is then transmitted to a central server for analysis. This setup helps in optimizing water usage and improving crop yield. LoRaWAN's low power consumption combined with solar-powered sensors reduces the overall energy requirements of the system which ensures that the sensors can operate sustainably over long periods without frequent battery replacements. The continuous monitoring and management of irrigation leads to better crop yields and the ability to make data-driven decisions enhances the overall productivity of the farm. Real-time data usage allows for precise irrigation scheduling, significantly reducing water wastage and ensuring optimal water usage for the crops. Automated monitoring and reduced manual intervention lower the operational costs. The long-range and low-cost nature of LoRaWAN makes it economically viable for large scale-deployment in agriculture.

VII. CONCLUSION

In this work, we have provided an in-depth analysis and compilation of device-level strategies for enhancing the energy efficiency of MTC. The comprehensive review has covered various subsystems, including the power, processing, sensing, and RF subsystems, highlighting trends, current and emerging, and technologies designed or modified for energy saving. The work identifies and discusses state-of-the-art technologies and strategies that have been developed to optimize energy usage in MTDs which include energy-efficient sensors, low-power processing units, and advanced communication protocols. By outlining the challenges encountered in implementing energy-efficient strategies, such as high energy consumption, computational complexity, and hardware limitations, the study provides a thorough understanding of the difficulties faced in each subsystem. It then explores potential solutions, tracing the evolution of technologies from early, less efficient methods to advanced techniques like modulation schemes, massive MIMO, and AI-driven optimization. Additionally, the discussion on future research areas and technological advancements offers valuable guidance for researchers and practitioners. By highlighting prospective paths for innovation with regards to the subsystems, the study aims to stimulate further research and development efforts, ultimately driving improvements in energy efficiency for MTDs.

Lastly, the inclusion of subsystem-specific case studies enhances the practical relevance of the work. These case studies demonstrate the effectiveness of current technologies and methods in real-world scenarios, providing a comprehensive understanding of how energy-efficient strategies can be successfully implemented. By addressing the identified gap and providing a detailed analysis of trends, challenges, and future directions, this work contributes significantly to the advancement of energy efficient MTC. The insights gained from this study not only enhance our understanding of current technologies but also pave the way for future developments that will further improve the sustainability and efficiency of MTC.

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