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Towards Energy Efficiency in the Internet of Wearable Things: A Systematic Review

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ABSTRACT Personal mobile devices such as smartwatches, smart jewelry, and smart clothes have launched a new trend in the Internet of Things (IoT) era, namely the Internet of Wearable Things (IoWT). These wearables are small IoT devices capable of sensing, storing, processing, and exchanging data to assist users by improving their everyday life tasks through various applications. However, the IoWT has also brought new challenges for the research community to address such as increasing demand for enhanced computational power, better communication capabilities, improved security and privacy features, reduced form factor, minimal weight, and better comfort. Most wearables are battery-powered devices that need to be recharged – therefore, the limited battery life remains the bottleneck leading to the need to enhance the energy efficiency of wearables, thus, becoming an active research area. This paper presents a survey of energy-efficient solutions proposed for diverse IoWT applications by following the systematic literature review method. The available techniques published from 2010 to 2020 are scrutinized, and the taxonomy of the available solutions is presented based on the targeted application area. Moreover, a comprehensive qualitative analysis compares the proposed studies in each application area in terms of their advantages, disadvantages, and main contributions. Furthermore, a list of the most significant performance parameters is provided. A more in-depth discussion of the main techniques to enhance wearables' energy efficiency is presented by highlighting the trade-offs involved. Finally, some potential future research directions are highlighted.

INDEX TERMS Wearables, Internet of Wearable Things, energy consumption, wearable applications, energy efficiency, computing, systematic literature review.

I. INTRODUCTION

The advent of small, inexpensive, and battery-powered computing units such as microprocessors and micro-controllers have paved the way for developing a wide variety of small form-factor devices that can be connected between each other and to the Internet. Such small devices form the basis of the Internet of Things (IoT) concept [1]. Millions of objects obtain a possibility to communicate over and to the Internet for seamless on-the-fly access and better control. However, more recently, the concept of smart devices worn and carried near the body, namely – wearables, has emerged forming the novel Internet of Wearable Things (IoWT) paradigm [2].

The IoWT or, similarly, the Wearable Internet of Things (WIoT) [3] is a merge of various smart wearable devices, as depicted in Fig. 1, including smartwatches, wrist bands, smart shoes, smart jewelry, smart glasses, adhesive skin patches, etc. Wearables are equipped with various

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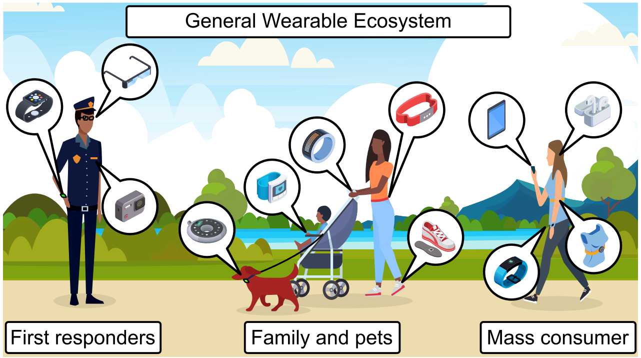

FIGURE 1. **Forthcoming wearable integration scenario.**

sensors, computing, and communication units, thus, enabling them to sense, process, and exchange various data types continuously [4].

Another very closely related research area is Wearable Body Sensor Networks (WBSNs) [5], [6] also known as Wireless Body Area Networks (WBANs) [7]. These areas mainly focus on human health-related applications and thus have some overlap with WIoT. However, there exists a subtle difference between WBSNs/WBANs and WIoT in the number of sensors/devices involved. WBSNs or WBANs usually aim to include a large number of wearable sensor nodes (up to 50 nodes) connected in the form of a network cooperating towards a common goal. For instance, multiple wearable sensor nodes collaborate to monitor an individual's overall health. Whereas, WIoT devices are often standalone ones currently being utilized for a wide range of applications, including health monitoring, observing human activities through localization and tracking, and various gaming and entertainment gadgets [8], [9]. Moreover, wearables also assist consumers in carrying out their everyday tasks more conveniently and efficiently employing visual and auditory stimuli [10], e.g., responding to incoming calls and messages, being notified of weather updates, and visualizing the timely vital information and many others [11]–[13]. Thus, broad adoption of wearables can revolutionize everyday human tasks and improve the overall quality of life [14], [15].

As of today, the consumers' interest in wearables proliferates enormously. The recent survey of the market trends indicates that wearable technology is expected to hit $ 52 billion by the end of 2020, which is around 27% higher compared to 2019 [16].

However, the paradigm focus shift from conventional smartphones towards smart wearables has also brought a plethora of research challenges to the scientific, research and industrial communities to be addressed. Besides the increase and versatility of the application areas, the growing demand for wearables' performance also arises. Today, wearables are still facing numerous limitations in several aspects such as computational power, communication capabilities, security & privacy features, form factor, weight, and comfort despite others [17], [18]. Still, the major bottleneck lies in the devices' limited battery life since wearables are mobile battery-powered devices according to numerous research works [19]–[21]. Therefore, the design of energy-efficient solutions for such devices is of utmost importance to prolong the wearables' battery lifetime while meeting the application's performance requirements.

Due to the increasing interest of the consumer market towards wearable devices, there have been significant contributions from the scientific and research community. Over the years, several attempts have been made to develop highly efficient solutions aiming to address the related challenges and exploit the full potential of wearable technology. Consequently, several survey papers have been published in the field. Some of them shed some light on wearable computing evolution as one of the potential solutions to solve the energy efficiency challenge of wearables.

For instance, work by Seneviratne *et al.* [8] presented a survey and classification of different commercially available wearable devices as per their functionality and wearability. It presents a general discussion on wearables' energy efficiency enumerating limited strategies, namely battery advancements, efficient sensing, and energy harvesting. Similarly, Rault *et al.* [22] published a survey of energy-efficient approaches for wearable sensor networks. However, the focus is limited to health-related human context recognition applications. Additionally, Williamson *et al.* [19] described the energy challenges for wearable sensing with a focus on the Miniature Micro-Electro-Mechanical (MEMS)-based inertial measurement units. Further, Sun *et al.* [23] provided a survey of the enabling communication technologies that can support wearable devices for current and future applications.

Moreover, some surveys focus on the use of wearables for a specific application such as health monitoring [24], activity recognition [25], [26], assisted living [27], mobile crowdsensing [28], smart garments [29], and indoor positioning [30].

In the studies mentioned above, none of the analyzed papers are explicitly focusing on the energy efficiency aspect and rather briefly mentioned the challenge in terms of energy requirements. Furthermore, a statistical analysis of the recent developments in the research field of energy efficiency in the IoWT was missing. Therefore, we provide a comprehensive survey of the state-of-the-art energy efficiency solutions for wearables following the systematic literature review methodology to fill in this gap in the IoWT technology.

The main contributions provided in this paper are:

1) Presenting a taxonomy of the IoWT solutions from an energy efficiency perspective based on the targeted application area classifying them into four categories: healthcare, activity recognition, smart environments, and general solutions.
2) Providing a qualitative and comparative analysis of existing studies and presenting their advantages, disadvantages, main performance parameters, and major contributions.
3) Summarizing the main findings about the techniques adopted in the literature to enhance wearables'

energy efficiency and highlighting the trade-offs involved.
4) Offering a statistical analysis of the available solutions in terms of year-wise publications, application areas, evaluation tools, simulation platforms, and communication technologies.
5) Identifying the potential challenges and future research directions concerning energy efficiency in the IoWT segment.

We achieve the mentioned contributions by answering the following research questions:

Q1. *What is the year-wise research trend related to the IoWT technology?*
Q2. *What are the current main application areas for the IoWT from an energy-efficiency perspective?*
Q3. *What are the primary performance parameters used to analyze and compare the performance of proposed energy-efficiency-related solutions?*
Q4. *What are the different performance evaluation tools used in the literature for the IoWT architectures?*
Q5. *What are the most commonly used wireless communication technologies in the IoWT?*
Q6. *What are the different techniques used in the literature to achieve energy efficiency in the IoWT?*
Q7. *What are the potential future research directions in the field of energy efficiency of the IoWT?*

The rest of the paper is organized as follows. The research methodology adopted for this Systematic Literature Review is explained in Section II. Next, Section III presents a detailed discussion of currently existing solutions utilized for different wearables applications (Q: 2,3) as well as statistical analysis and discussion on state-of-the-art research done in the IoWT field (Q: 1,2,4,5). Strategies to improve energy efficiency in wearables are presented in Section IV (Q: 6). Further, Section V outlines the main challenges, potential future research directions, and related discussion (Q: 7). Finally, the summary of the review is drawn in the last section.

II. RESEARCH METHODOLOGY

This section discusses the research methodology adopted to carry out this systematic literature review, which is based on the PRISMA guidelines, proposed in [31].

The initial step was to identify the appropriate keywords and associated synonyms to form a search expression. After brief analysis of the literature, the following search expression was formed:

> (“energy efficien*” OR “energy conserv*”
> OR “low power”)
> AND (wearable*)
> AND (edge OR cloud OR fog OR approximate OR
> IoT OR “Internet of Things” OR performance)

A search was performed with the selected keywords for the 2010 – 2020 period in the two most widely accepted research databases in Information and Communications Technology (ICT) domain, namely Scopus [32] and Web of Science [33]. We gathered a set of 2370 potentially relevant publications (as of July 2020), excluding grey literature, pre-prints, and duplicates. We then analyzed the titles, keywords, and abstracts of the publications in order to identify papers and articles that described at least topics related to the energy efficiency/consumption in the IoWT field. The following exclusion criteria were developed to refine the search results during the paper titles and abstracts’ initial screening:

C1. Not related to wearable networks/computing;
C2. Pure survey and review articles;
C3. Works with no technical content;
C4. Full text not available.

The entire selection process is given in Fig. 2. After applying the aforementioned refinement procedures, we lowered the articles number to 50 potentially relevant papers. After analyzing the selected literature references and citations, we increased the number to 151 works to be included in the core and discussion of this systematic review on energy efficiency in the IoWT.

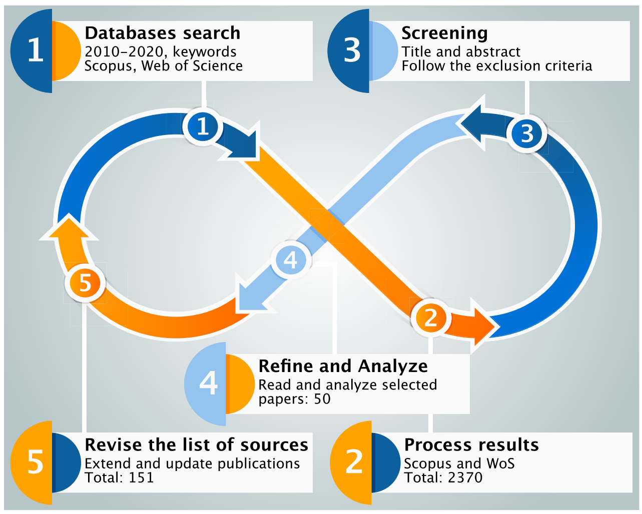

FIGURE 2. The main steps involved in the executed systematic literature review process.

III. CLASSIFICATION OF EXISTING APPLICATIONS AND RELATED TECHNOLOGIES

This section presents a classification, statistical analysis, and qualitative analysis of the selected papers. The yearly distribution is provided in Fig. 3. It can be observed that there is an increasing trend in the number of publications in the IoWT domain while some works from 2019 and 2020 may still be not indexed or under review.

Based on the targeted application area, the selected papers were classified into four main categories, namely, healthcare, activity recognition, smart environments, and general solutions. Fig. 4 presents a statistical analysis of different application areas in wearable technology. Within each of them, specific applications are considered to benefit from IoWT energy-efficient technologies, as depicted in Fig. 5.

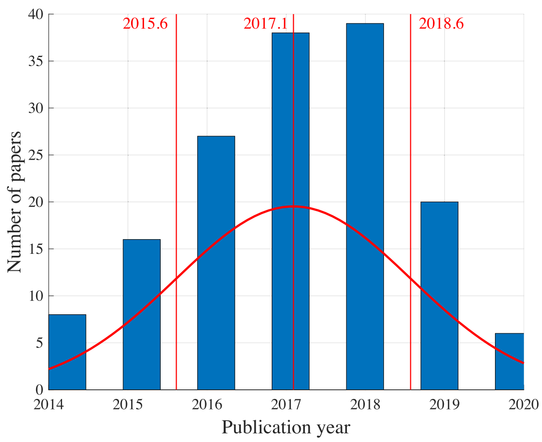

FIGURE 3. Year-wise distribution of number of articles analyzed: Red Lines correspond to mean and mean +/− standard deviation.

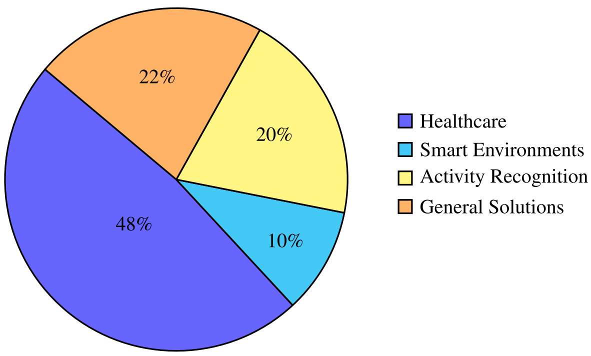

FIGURE 4. Percentage of works targeting each application area in the analysed literature.

Due to the fact that many consumer wearable devices historically appeared in the healthcare field for continuous observation of patients [34], a plethora of research papers fall under the *healthcare* category with a share of about 48%. Here, wearables were mostly used to monitor vital human signs. The above-mentioned trend can be explained by the fact that wearables were initially developed for specific medical purposes such as continuous monitoring of human heart activity through the Electrocardiography (ECG), hearing devices for the deaf, robotic limbs for the medically paralyzed patients, etc.

Evidently, wearables have found applications in many other domains apart from healthcare over time. For instance, research focusing on human activity recognition contributed as much as 20%. Activity recognition can be used to monitor and keep track of human physical movements. For example, wearables have been increasingly used to provide several user activity-based services such as suggesting areas of interest, activity-based fitness recommendations through step counting, and tracking the user's sports activities [35], [36]. Similarly, wearables have also been used to provide location-based services [37], gesture recognition applications [38], and monitoring industrial workers [39]. Therefore, all such studies that utilized wearables for tracking user activity are grouped under the *activity recognition* category.

Many research studies provided general IoT-based solutions using wearables that can be adopted in different application areas. The percentage of such solutions contributes about 22%. Moreover, wearables were also adopted in some other application areas such as Smart Environments, with a share of 10%.

Additionally, wearables have found applications in the *Smart Environments* domain. For example, the use of wearables has been proposed in smart buildings to monitor and minimize electricity use by automatically powering off unnecessary electrical equipment through real-time monitoring of the occupants and environment [40], [41]. Similarly, some studies utilize wearables to assess and optimize users' thermal comfort level in a smart environment by continuously monitoring the temperatures and automatically controlling the heating/cooling systems [42]. Moreover, wearables can also be used to assist persons with disabilities enabling them to carry out their daily activities more independently [43]. Therefore, all such studies that utilize wearables for applications in the smart environment concept are grouped under this category.

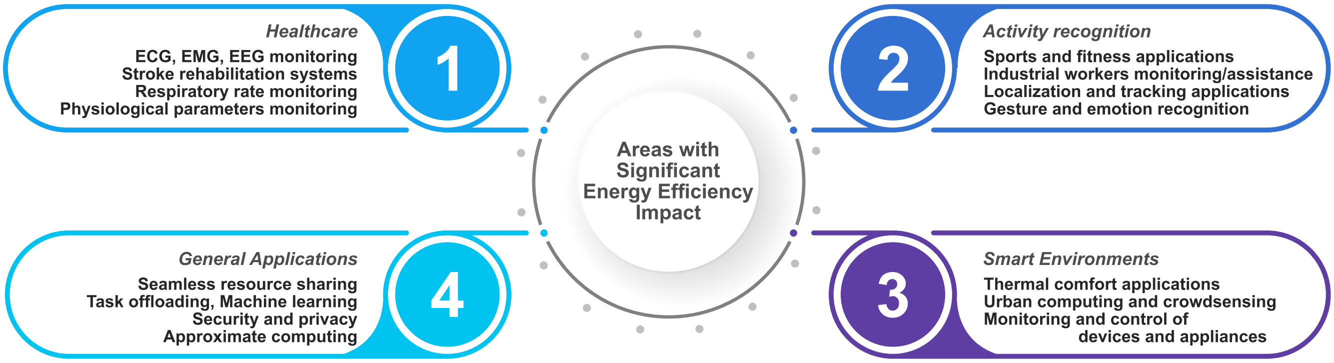

FIGURE 5. Main application domains of wearables with high energy-efficiency impact.

Finally, some studies either do not specify the application area or are claimed to be suitable for multiple application areas. Such studies are grouped under the *general solutions* category, i.e., the researchers were generally elaborating on the technology, enablers, or strategies without the focus on any specific application area.

A discussion on each classification category's specifics is provided along with qualitative and performance analysis of papers falling under each category in the following subsections. We provide a summary of the identified solutions by presenting the aim, advantages, disadvantages, and major findings for each application area in Tables 1, 3, 5, and 7. Moreover, we present a comparative evaluation of solutions in terms of the main considered performance parameters for each application area including traditional common Key Performance Indicators (KPIs) parameters, e.g., latency, energy consumption, and throughput, as well as specific ones in Tables 2, 4, 6, and 8. Note, the tables only provide acronyms instead of the terms' introduction in order to save space and for better readability. The taxonomy of frequently used acronyms is given before the references' list.

It is worth noting that there are some application area-specific performance parameters present for different areas. The healthcare area also focuses on *Signal Reconstruction Quality*, which is a measure of how accurately a signal is reconstructed at the gateway node based on the recorded observations through sensors. *Network Lifetime* is another parameter that defines the operating duration of a network until one of its nodes depletes its energy. Furthermore, the *Signal to Noise Ratio (SNR)* provides the relative strength of the desired signal compared to noise level. Moreover, *Compression Ratio* is a parameter that shows the degree to which a data set is compressed. Finally, *Reliability* is given as the probability of failure in the system.

Additionally, the *Sensitivity* metric is used in the activity recognition applications providing the ability for a wearable device to detect any activity by the user instantly. Moreover, the *Video Quality* parameter is used in smart environments for crowdsensing applications. Finally, *Execution Time* and *Transmission Time* are considered in general solutions showing the measure of how fast a wearable device performs computations and how quickly it can transmit the data to a gateway node.

The following subsections detail the applications along with the related performance metrics.

A. HEALTHCARE APPLICATIONS

Recently, the advent of the IoWT technology and advances in wireless communication have revolutionized the medical field [68]. Moreover, due to the miniaturization of various sensors, several smart healthcare devices have been developed that are easy to use and carry while at the same time are capable of connecting to the Internet to access the cloud services. These include wearable devices for continuous patient monitoring inside hospitals [45] and several small gadgets that continuously sense and keep track of individuals' various health indicators during their everyday routine [51]. Wearables under the healthcare applications domain cover solutions such as heart and respiratory rate monitoring systems [56], stroke rehabilitation systems [53], and monitoring heart, muscle, and brain activities through the ECG, Electromyography (EMG), and Electroencephalography (EEG) signals [69]. Several wearable devices have been developed to continuously sense and measure various physiological parameters of humans and animals, including heart rate, blood pressure, body temperature, stress hormones among others [52].

The IoWT concept enables remote patient monitoring systems where a patient carries one or more wearable devices that continuously monitor the patient's health and record the measurements in online databases to be assessed by the patient's doctor. Automated help-seeking solutions are also proposed for an emergency case, e.g., a call could be initiated to the caretaker/medical staff [70].

From Table 2, it can be observed that the most commonly monitored performance parameter is energy consumption, followed by accuracy, latency, and throughput. The reliability factor was found to be the least analyzed in the context of wearables for healthcare. Interestingly, since most healthcare wearables rely on continuously sensing various physiological parameters (as explained above), the devices deplete their energy due to excessive sensing, and redundant data generation consuming much time. Therefore, strategies such as compressive sensing and data compression are very efficient for energy conservation in healthcare applications [71]. These strategies are discussed in more detail in Section III-E.

B. ACTIVITY RECOGNITION APPLICATIONS

Over the past decades, wearables were increasingly used for various activity recognition applications [72]–[74]. Due to the miniaturization of electronic equipment, it became possible to integrate several sensors in a single wearable device such as accelerometers, gyroscopes, magnetometers, heart-rate sensors, etc. Those devices are used to sense different human activities [75]. Many applications rely on the continuous monitoring and recording of human activities such as fitness levels based on user's sports activities, areas of interest by keeping records of the most visited sites, fall detection, sleep, and fatigue detection, gesture recognition, emotion recognition, housekeeping, and so on [76]–[78]. Similarly, wearables have also been used to track the activities as well as assist workers in their workplaces for improved performance [79].

Similarly, wearables are also applied in habitat monitoring [80]. For example, monitoring the activities and behaviors of animals in their natural environment, taking care of pets, tracking the flying patterns of birds, and so on [81], [82].

The most commonly studied performance parameters in the activity monitoring domain are energy consumption and accuracy, according to Table 4. The latency, battery lifetime, and sensitivity were not so frequently analyzed.

Most activity recognition wearables rely on continuously sensing various subjects' physical movements through

TABLE 1. Summary of recent studies in healthcare domain.

Ref.	Aim of study & Major findings	Merits	Demerits
[44] 2020	Real time compressive sensing-based recovery of the ECG signals at the IoT gateway using multicore processors	Improved latency, privacy and energy efficiency; independent on cloud infrastructures	Only suitable for sparse signals
[45] 2019	An IoT architecture relaying on open standards (oneM2M and openEHR) and allowing for the interoperability between different devices and software to track physiological parameters of patients in emergency wards	Interoperability, low latency, low cost, enhanced battery lifetime, efficient ESP8266 Wi-Fi nodes	No real-time validation, high latency with deep sleep states
[46] 2019	An energy-efficient data-criticality aware routing protocol for WBANs	Enhanced network lifetime, emergency data delivery	No mobility support, single point of failure
[47] 2019	A wearable cardiovascular healthcare system with cross-layer optimization comprising an efficient sensing patch with embedded signal denoising, data compression, and data transmission capabilities	Miniaturized footprint, low power consumption, embedded signal processing capability	Low accuracy on the mobile device side
[48] 2018	A wearable ring sensor for monitoring autonomic nervous system activities	Small size, ease of use, low cost, mobile application	No comparison with other devices
[49] 2018	A Markov decision process-based transmission strategy for multi-hop intra-BAN communication	Adaptive transmission power optimization	Limited performance comparisons
[50] 2018	An efficient next-hop node selection framework based on multi-parameter path cost function WBAN	Energy-efficient, low packet loss, high throughput and extended network lifetime	Control messages overhead, human body movement not considered
[51] 2018	A wrist-worn ECG sensor measuring heart rate variability in out-of-the-clinic settings with 3D printed elements for personalization, capable of integrating with the Azure IoT system	Low power, low weight, personalized features	Low accuracy
[52] 2018	A wearable ring sensor with an iOS application for remotely monitoring parameters of patients, e.g., electrodermal activity, heart rate, locomotion, temperature	Compact and miniaturized design, low cost, recording various bio-signals from user's finger, high accuracy	High motion artifacts
[53] 2018	An IoT-based smart wearable armband for stroke rehabilitation system deploying ML algorithms to strengthen the motion patterns	Mobility support, small size, real-time feedback of muscle activities, personalization with 3D printed robotic hand	Tested on a single subject, limited gesture recognition supported
[54] 2018	A mobile real-time health monitoring architecture based on a heterogeneous multicore platform for ECG signal processing	Enhanced battery life, low latency, low power device design	Sub-optimal performance for clinical-grade signals due to frequent transmissions
[55] 2017	A dictionary-based lossy signal compression technique for enhancing energy efficiency of wearables	Energy-efficient, high compression efficiency	High computation cost
[56] 2017	A low-power wearable device for continuous respiratory rate monitoring using a three-axis accelerometer from the sternum with an integrated motion artifact rejection algorithm	Efficient motion artifact rejection to remove noisy data	Limited mobility, not easy-to-use, limited battery life, no real-world testing
[57] 2017	A data-driven compressive sensing framework that can learn signal characteristics and personalized features from physiological signals	Low computational complexity, improved compression ratio	No real-time validation provided
[58] 2017	A compressed sensing-based multi-channel EEG monitoring system with efficient signal compression and recovery	No prior knowledge of the signal sparsity required, improved reconstruction quality, robust	No real-time validation provided
[59] 2016	A 6LoWPAN-enabled WBAN platform with 6 different biomedical sensors optimized to meet the QoS requirements for healthcare applications	High throughput, low power, scalability, interoperability, low latency	Vulnerability to obstacles, high packet collisions
[60] 2015	An IEEE 802.15.4 based QoS design for WBAN MAC layer with beacon mode deploying tree topology supporting high-priority data transmissions	Energy-efficient, incorporating data priority feature for critical data	Starvation problem faced by low priority nodes not considered
[61] 2016	A multihop WBAN configuration approach by creating a virtual cluster to allocate slots for simultaneous transmissions by using a multi-channel TDMA approach for wearable M2M systems	Enhanced throughput, low power consumption, low latency, better scalability	Initial setup time increases exponentially with number of nodes
[62] 2017	A configurable bio-signal acquisition wearable device for real-time monitoring on an IoT based web interface with a balanced trade-off between energy efficiency and data transmission rate	High data rate, low energy consumption, compact design	Bulky, not easy-to-use
[63] 2015	A web-based motion detection system for healthcare	Real-time bidirectional communication	High resource consumption, false alarms, lack of analysis
[64] 2018	A patient monitoring systems deploying relay-based task offloading decision model with the efficient recipient selection function	Low path loss, high computation capacity, locally processed packets	No experimental validation
[65] 2016	A wearable armband with a mobile application for unobstructed measurement of the ECG signal	Multiple activities support (sitting, hand movement, jogging, and running)	No validation on multiple subjects, high error rate
[66] 2016	A 3D Ray Launching deterministic simulation tool for feasibility and performance optimization of the WBAN-based e-Health systems within complex indoor scenarios	Low processing time, high accuracy, optimal estimation of number and position of transmitters	Patient mobility not considered
[67] 2015	A CPS for remote monitoring of old age home residents in real-world scenarios	Secure, scalable, low power, low cost, easy deployment	High latency, increased energy consumption due to the MAC retry attempts

TABLE 2. Main parameters considered by recent studies in healthcare.

Ref.	Energy Consumption	Signal reconstruction quality	Latency	Network Lifetime	Throughput	Accuracy	SNR	Compre-ssion ratio	Reliability
[44]	✔	✔							
[45]	✔		✔	✔					
[46]			✔	✔	✔				
[47]	✔					✔	✔	✔	
[48]	✔					✔			
[49]	✔				✔				
[50]	✔			✔	✔				
[51]						✔			
[52]						✔			
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[58]		✔							
[59]	✔		✔		✔				
[60]			✔		✔				
[61]	✔		✔		✔				
[62]	✔				✔				
[63]	✔		✔						
[64]	✔		✔	✔	✔				
[65]						✔			
[66]							✔		
[67]									✔

different sensors that produce raw data. These recordings need to be processed and analyzed for feature extraction and classification to accurately detect activities of interest through sophisticated Machine Learning (ML) techniques that often require high computing capabilities [93], [94]. Since wearables are autonomous devices with limited computational power, various strategies such as task offloading, low power hardware design, data compression, and approximate computing are very efficient for energy conservation in activity recognition domain.

C. SMART ENVIRONMENT APPLICATIONS

Recently, wearables have gained much attention for a wide range of the IoT applications, especially in a broad smart environment area where automation is brought close to the users. Smart environments include smart cities, smart buildings, smart homes, smart transportation, etc., for enhanced urban development to improve the overall quality of life [100]. For instance, wearables can be used to optimize heat and electricity management in smart buildings where heat and electricity can be managed for optimal user experience and resource-saving [101].

Furthermore, mobile crowdsensing is another very active area of research involving wearables, where users generate mass volumes of data through collectively sensing and sharing gathered data of common interest in smart cities [102].

Similarly, wearables can be applied for controlling home appliances in smart homes. For example, with wearables, it is possible to authorize individuals' access to shared appliances, such as refrigerators, washing machines, or shared living areas like hostels and student apartments, etc. Moreover, it can also help track when an individual used a particular appliance for a fair distribution of electricity usage among residents.

Table 6 shows that the most commonly analyzed performance parameters, besides latency, throughput, and video quality, are energy consumption and accuracy.

D. GENERAL SOLUTIONS FOR WEARABLE APPLICATIONS

Wearables are currently being used for a wide range of new applications apart from the conventional application areas. Similarly, there is a trend to propose general-purpose solutions that could be tuned for any specific application.

For instance, Nakhkash *et al.* [103] provided the energy consumption profiles of various IoT applications running on resource-constrained wearables and proposed the efficacy of software approximations for maximizing energy and performance gains.

Similarly, the work by Golkarifard *et al.* [104] proposed a generic code/task offloading scheme for wearables to utilize computing resources of cloud and nearby devices. The authors elaborated on a generic task scheduler that dynamically classifies tasks for local and remote processing.

TABLE 3. Summary of recent studies in activity recognition domain.

Ref.	Aim of study & Major findings	Merits	Demerits
[83] 2019	A framework to co-optimize the operation of sensors and classifiers by dynamically controlling the sampling rate and powering down accelerometer sensors for low-intensity user activities	High accuracy, low power consumption	Not suitable for high-intensity user activities
[84] 2019	An embedded deep CNN multimodal time-series signal classification scheme	Low power, scalable	Complex implementation
[85] 2018	An IoT-based solution for apportioning of the total energy consumption of a household to individual occupants	Accurate, scalable, privacy-preserving	No energy apportioning for heating, ventilation, and air conditioning
[86] 2017	A context-aware framework to offload tasks from wearables to the gateway and cloud	Low latency for interactive user tasks, low energy consumption for tasks unrelated to user interaction	Not tested with a battery-operated smartphone (only with an external power supply)
[87] 2017	An adaptive compressed sensing framework for coarse-grained activity recognition to find an optimal trade-off between compression ratio of each activity type and the overall performance of the activity recognition system through feedback	High accuracy, low power, autonomous feedback system, adaptive activity-specific compressed sensing	Additional processing cost for on-node feedback generation
[88] 2017	A lightweight and low-profile wearable monitoring system for long-term activity monitoring and recognition using two accelerometers instead of a gyroscope as a low power alternative	Low power, high indoor efficiency, accessible to use (wrist-worn)	Dummy data used for processing
[89] 2016	A generalized activity recognition algorithm for implementation in wearables facilitating activity-based communication for the connected industrial worker	Computationally inexpensive, memory-efficient, user-independent	Transition between states is not detected efficiently
[90] 2018	A prototype for emotion recognition system based on low power SoC inside a tiny wearable device using ad hoc simplification	Low complexity, low computational resources	Low accuracy
[91] 2019	A communication network edge maintenance system based on smart wearable technology. It uses a MCSS algorithm for task division and KM for accessing a MEC server	Reduced transmission delay and energy consumption, efficiency of on-site maintenance work	Technological aspects of the used wearable device not provided
[92] 2016	A gesture recognition systems for industrial workers with a ML model using a wrist-worn wearable device	Reduced computational complexity, user-independent	No analysis for the scarce resources availability on the wearable device

TABLE 4. Main parameters considered by recent studies in activity recognition domain.

Ref.	Energy Consumption	Accuracy	Latency	Battery Lifetime	Sensitivity
[83]	✔	✔			
[84]	✔	✔			
[85]		✔			
[86]	✔		✔		
[87]	✔	✔			
[88]	✔			✔	
[89]		✔			
[90]		✔			✔
[91]	✔		✔	✔	
[92]		✔			

Song *et al.* [107] outlined the software engineering support for appflication developers to utilize shared resources between mobile devices for optimal performance through seamless resource sharing to enhance programmer's productivity as well as reduce energy consumption and execution time of devices.

Additionally, some studies propose using low power hardware for the development of future wearables by providing the overall energy consumption profile, and achieved energy savings [108], [112].

Furthermore, there has been an increasing trend towards proposing generic ML techniques for wearables targetting different applications. For example, Xu *et al.* [113] proposed a generic deep learning framework for wearables to achieve improvements in their performance and energy consumption. They advocate that since wearables are capable of collecting a wide spectrum of data, including user activity-related data, healthcare-related data, fitness tracking, etc., the possibility to collect such unique data creates countless applications for deep learning.

For these application areas, energy consumption is the most commonly considered performance parameter, followed by latency, throughput, and execution time, as listed in Table 8. The other parameters such as network lifetime, transmission time, and accuracy are rarely analyzed.

TABLE 5. Summary of recent studies providing solutions for Smart Environments domain.

Ref.	Aim of study & Major findings	Merits	Demerits
[95] 2017	A SoC wearable integrating brain signals to control the HVAC system and other home devices (lights, fan) through the voluntary eye blinks	Low power, low complexity, low error rate	Bulky, not easy-to-use in everyday life, limited appliances to control
[96] 2014	A low-power resource-preserving MAC protocol for resource-constrained wearables	Reliable, scalable, low power	No analysis provided for the latency
[97] 2016	An optimization algorithm for cloud-based video crowdsensing using resource-constrained wearables and mobile devices	Higher perceived video quality, energy efficient storage, reduced delivery delay, and higher average throughput	Not suitable for applications requiring high video quality
[98] 2016	A wearable, light-energy-harvesting-assisted sensing, processing and decision-taking RFID tag for integration with a smart garment	High read range, enhanced functionality, flexible interfacing, diverse low-power sensors	High cost and power consumption of the RFID tag
[99] 2018	A framework for monitoring thermal conditions in a building through the use of wearable solutions, parametric models, and the ML techniques through analyzing specific psychophysical conditions	Detection of internal environmental variables close to users, biometric parameters	Limited factors to assess the thermal comfort

TABLE 6. Main parameters considered by recent studies in Smart Environments domain.

Ref.	Energy Consumption	Accuracy	Latency	Throughput	Video quality
[95]		✔			
[96]	✔			✔	
[97]	✔		✔		✔
[98]	✔	✔			
[99]		✔			

E. SECTION SUMMARY

This subsection provides the main summary and discussion of the statistical data based on the systematic literature review results.

First, Fig. 6 presents a statistical analysis of the evaluation methods found in the literature to assess the performance of newly proposed solutions and compare them with other already existing solutions. The methods mainly include performance comparisons through simulations or real-time experiments on prototypes or a combination of both simulation results and their validation through real-time experiments on prototypes.

As per the recorded statistics from the relevant papers, it has been observed that 58% of the studies carried out experiments on real prototypes only. 23% of the studies were simulation-based with no real-time validation. Also, 19% provided performance evaluation of the proposed solutions through both simulations and validation through real-time experiments on prototypes.

Inspired by [114], Table 9 highlights some wearable devices listed in the prototype-oriented papers from the energy efficiency perspective. It has been observed that most of the works focused on developing research-based prototypes to emulate a wearable device for their proposed solutions in the attempt to develop more efficient devices, rather than experimenting with the wearable devices available on market. Based on the literature, we have presented the energy consumption profile (classified as low, medium, high) of various wearables.

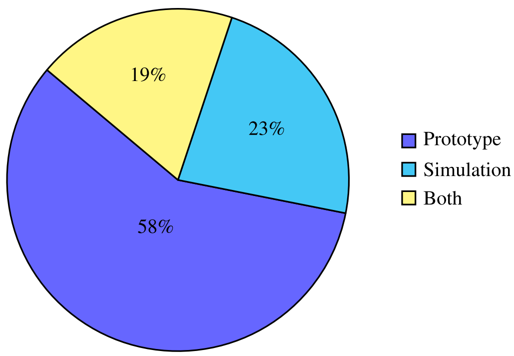

FIGURE 6. Percentage of the evaluation methods used in the analysed literature.

Here, most of the devices used in healthcare and activity recognition application areas have a low-medium energy consumption profile, due to their low data rate and low-power hardware to fulfill the extended operation time requirement. At the same time, some solutions in the smart environment and general-application categories have medium-to-high energy-consumption profiles, due to the application requirements demanding high data rates and complex processing.

Furthermore, since a significant share of the scientific community relies on simulation-based studies, researchers need to know the existing trend in the choice of simulators used in the field. For this purpose, we collected statistics on the different types of network simulators utilized in the

TABLE 7. Summary of recent studies providing general solutions using wearables.

Ref.	Aim of study & Major findings	Merits	Demerits
[103] 2019	Leveraging error resiliency of the IoT applications to trade accuracy for performance and energy gains through software approximations at different phases of sensing, computation, and transmission	Analytical modeling and characterization of various IoT applications, real-time hardware evaluation	Can not be generalized for any IoT application
[104] 2018	A unified code offloading system for wearable computing to leverage computation resources of nearby and cloud systems with a reference implementation on Google Glass	Programmer-friendly framework, lightweight offloading, run time task scheduler for the decisions, energy-efficient, fast execution, error recovery support	Not suitable for crowded and large environments such as shopping malls resulting in high failure rate even with lots of nearby devices
[105] 2019	A comparison of performance and energy consumption of various platform boards emulating wearables to investigate a best offloading approach for improved QoS for the IoT applications. It proves that offloading computationally intense tasks to a powerful node improves QoS but not always valid for data-intensive tasks	Multithreading, classification of tasks for improved QoS	Communication overhead in terms of power consumption not considered
[106] 2019	An Android-based application for wearables whose tasks can be partitioned between a wearable, MCC, and Fog computing	Enhanced battery lifetime, access to high computing and storage resources of fog and cloud servers	Additional overhead in terms of communication due to the task offloading
[107] 2018	A software engineering support for application developers to leverage the shared resources between heterogeneous mobile devices	Seamless, reliable, and efficient resource sharing among devices	Significant communication overhead for large packets
[108] 2017	Using wake up radios with the BLE transceivers to minimize the energy consumption due to continuous listening	Low energy consumption	Extra hardware cost, no hardware implementation to verify results
[109] 2017	An adaptive channel connection interval for the BLE devices to improve connectivity and energy consumption	Low energy consumption, improved connectivity	The channel link quality assessment overhead, proprietary BLE controllers do not allow such implementations
[110] 2016	A content agnostic privacy and encryption protocol eliminating the need for asymmetric encryption for wearables	Energy-efficient	Limited threat models
[111] 2016	A power aware multi-hop dynamic source routing mechanism for MANET designed for the BLE-based sensor networks	Enhanced lifetime, high throughput	High latency
[112] 2015	A simple and reliable bidirectional communication protocol for communication between the transmitter module (nRF24) and the BLE devices by using advertisement frames	Improved reliability	Increased latency, additional communications overhead, decreased throughput
[113] 2019	A practical deep learning-based framework for improving the performance of wearables	Improved end-to-end latency, robust to the privacy breach, energy-efficient	Memory overheads not considered, the handheld device limited processing capacity can reduce the performance

TABLE 8. Main parameters considered by recent studies providing general solutions for wearable applications.

Ref.	Energy Consumption	Latency	Network Lifetime	Throughput	Execution time	Transmission time	Accuracy
[103]	✔						
[104]	✔				✔		
[105]	✔				✔		
[106]	✔				✔		
[107]	✔	✔					
[108]	✔	✔					
[109]	✔						✔
[110]	✔					✔	
[111]			✔	✔			
[112]				✔			
[113]	✔	✔		✔	✔		

surveyed literature and their percentages of use. The collected statistics are presented in Fig. 7. It has been observed that MATLAB [115] has the highest share (around 50%). Several other network simulators were also used, namely Network Simulator 2 [116], OPNET [117], OMNeT++ [118], and Castalia [119]. All of the listed network simulators were equally popular among the scientific community, with an equal share of about 5%. Some researchers used custom-built simulators, including C++ and Java-based, with a share of 10%.

TABLE 9. Examples of wearable devices per application area.

App. area	Ref.	Purpose	Wearability	Wearable devices / Research prototypes	Energy Profile
HC	[48]	Autonomic nervous system activities	Finger worn	A ring sensor	L
HC	[53]	Stroke rehabilitation	Upper arm	Armband	L–M
HC	[51]	Heart rate variability monitoring	Wrist worn	Custom made wrist wearable ECG sensor	L
HC	[47]	Cardiovascular healthcare system	Chest worn	Customized SoC based ECG sensing patch	L
HC	[56]	Respiratory rate monitoring	Abdomen	A custom made wearable device with 3-axis accelerometer	L–M
HC	[62]	A configurable bio-signal acquisition device	*NA*	A custom made multi channel device capable of acquiring ECG, EMG, and EEG signals	L–M
HC	[55]	A lossy signal compression technique for biosignals on wearables	Chest and wrist worn	Zephyr BioHarness 3 wearable device	L
HC	[59]	A multi sensor 6LoWPAN-enabled WBAN platform	*NA*	Multiple Zolertia sensor motes connected to a main Cubox device	L
HC	[63]	A web-based motion detection system using wearables	Carried in pocket	Zolertia Z1 motes emulating wearables	M–H
AR	[92]	Gesture recognition system for industrial workers	Wrist worn	A custom-built wearable device containing accelerometer and gyroscope sensors	L–M
AR	[87]	Activity recognition	Torso	A 3D motion tracker	L
AR	[83]	Low intensity activity recognition	Knee worn	A custom prototype using an accelerometer as a motion sensor and stretch sensor	L
AR	[90]	An emotion recognition system	Not specified	A custom built wearable prototype including PhotoPlethysmoGraphy (PPG), Galvanic Skin Response (GSR), and Skin temperature (SK) sensors	L
AR	[89]	Activity recognition for industrial workers using wearables	Sacrum worn	A custom-built wearable device using Bosch's BMI 160 containing accelerometer and gyroscope sensors	L
AR	[88]	A wearable system for long-term activity monitoring and recognition	Wrist worn	An nRF51822 System on Chip (SoC) with two ADXL362 accelerometers	L
SE	[98]	A wearable RFID tag for smart garments enabling seamless interaction of wearer with other smart devices	Any on-body garment	A custom made circular patch antenna with integrated sensing, processing, and transceiver hardware	L
SE	[97]	Cloud-based video crowdsensing using wearables	Head mounted	Raspberry Pi with a camera module to emulate a wearable device	M–H
SE	[95]	Using EEG signals to control the HVAC system and other home appliances	Forehead mounted	Custom SoC based wearable EEG sensor	L–M
SE	[99]	Monitoring thermal conditions in buildings through wearables	Wrist worn	Empatica E4 wristband	L–M
GA	[103]	Approximating IoT applications for wearables	*NA*	Raspberry Pi Zero emulating a wearable	L
GA	[104]	Code offloading system for a wearable application to extract text information from the ambient environment	Face worn	Google glass	M–H
GA	[113]	Task offloading for wearables	Wrist worn	Smart watch	L–M
GA	[112]	A two-way communication protocol for wearables	*NA*	An nRF24 SoC emulating a wearable device paired with an iPhone 5s	L
GA	[111]	Multihop routing algorithm for BLE enabled wearables	*NA*	Broadcom combo chipset BCM434X for BLE enabled sensors emulating wearables	L
GA	[109]	Efficient connection maintenance technique for dynamic wireless channels	*NA*	A custom built prototype using Raspberry Pi	L

HC – Healthcare AR – Activity recognition SE – Smart Environments GA – General Applications
L – Low M – Medium H – High

Finally, some of the studies did not report the tool used for the simulations, which were about 20%. This high fragmentation would suggest the design of a simulation tool specifically conceived for the IoWT well recognized by the community and favoring the reproducibility of results.

Although the communication technology choice is affected by the application area with specific requirements and associated constraints, it is significant to highlight that the most commonly used communication technologies operate on a short range. The collected statistics regarding the wireless technology used in different works are presented in Fig. 8. Bluetooth (including Bluetooth Low Energy (BLE)) is the most common short-range communication technology in the field, with a share of about 46%. Zigbee is also used in many applications with a share of 15%, followed by Wi-Fi with 9%. Furthermore, some proposed solutions use a combination of these communication technologies. Such techniques are referred to as hybrid and contribute 9%. The IEEE 802.15.6, also referred to as WBANs, was found to have a share of 6%. Finally, solutions that do not specify the communication technology contribute 15%.

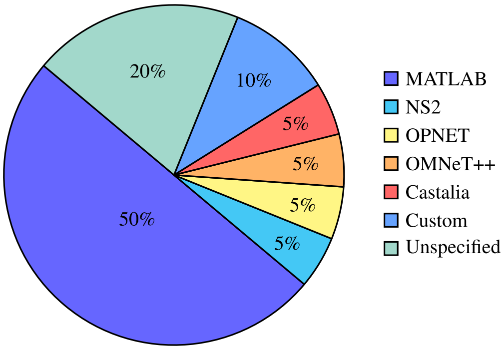

FIGURE 7. Percentage of the network simulators used in the analysed literature.

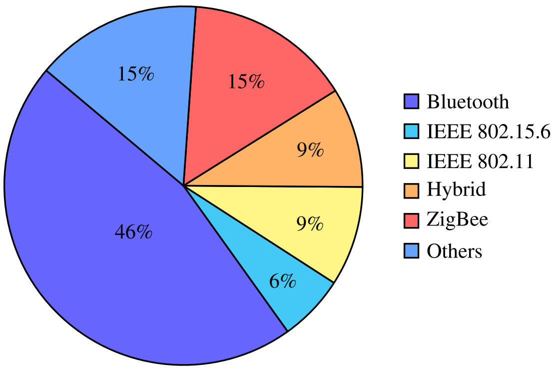

FIGURE 8. Percentage of the communication technologies used in the analysed literature.

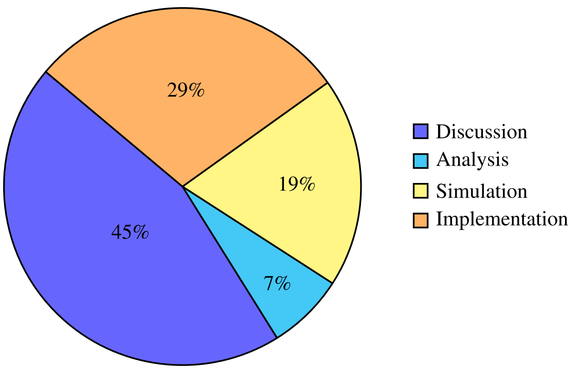

FIGURE 9. Distribution of the energy-efficiency analysis elaboration in the analyzed papers.

Finally, the papers were analyzed from the energy-efficiency focus perspective, i.e., the depth of the discussed systems evaluation, as shown in Fig. 9. Based on the observation, it could be concluded that most of the works highlight the problem of energy efficiency at a theoretical level without providing any metrics that could be directly converted into energy-related ones. Interestingly, a significant portion of researchers (29%) has performed prototyping and measurements of the proposed energy-efficient strategies.

IV. STRATEGIES TO IMPROVE ENERGY EFFICIENCY OF WEARABLES

In this section, we present a detailed discussion of the main techniques adopted in the surveyed literature to achieve better energy efficiency in wearable devices and related communications networks based on our systematic review.

A. TASK OFFLOADING

Many resource-hungry applications involve computationally intensive tasks such as deep learning techniques for activity recognition, etc. Those can shorten the battery life of wearable devices and, therefore, computational task offloading, i.e., when the offloaded tasks are executed remotely in, e.g., cloud to reduce the processing and energy consumption of the mobile device, has been extensively used in the literature to achieve energy efficiency in wearables [86], [120], [121]. Conventionally, task offloading relies on using cloud services to process computationally expensive tasks. However, it involves substantial transmission delays that sometimes could not meet many IoT applications' strict latency requirements [122], [123].

Additionally, the unavailability of stable Internet connection was another problem for the task offloading [104]. Today's handheld devices, such as smartphones, are equipped with more powerful chipsets with multicore processors that have the potential to be an efficient alternative. Therefore, utilizing edge computing [124] and fog computing [125] techniques to use the resources of nearby mobile and gateway devices has proved to be very beneficial for resource-constrained wearable devices both in terms of energy consumption as well as performance [126]–[128].

Another benefit of the computation offloading lies in the fact that most of the available wearable devices are equipped with low-power short-range communication technologies such as BLE that eliminate the dependency on the actual direct Internet connectivity. However, the downside is increased latency [129]. Another complexity lies in the effective splitting of tasks into locally- and remotely executable tasks that could run independently on nearby devices [105]. Therefore, task offloading may work effectively for delay-tolerant applications to minimize energy consumption. Whereas, it might not be a practical option for other applications with strict latency requirements.

B. DUTY CYCLING

Wearable devices commonly have a computation unit with storage, a communication unit, and several sensors onboard for their operation [3]. All these modules contribute significantly to the wearable device's overall energy consumption if they remain active all the time. However, there are several applications in which all of these units are not so frequently used. Some of these are long term environmental monitoring [130], smart agriculture and livestock monitoring [131], and long term healthcare applications [132], [133], etc.

Therefore, duty cycling is another approach used to conserve energy by powering off all or major hardware modules of the wearables or making them enter sleep mode when not in use to minimize the wearable device's overall energy consumption. This optimization requires efficiently identifying the duration and timing of the sleep cycles. Otherwise, it could negatively affect the wearable device's performance in terms of execution speed, responsiveness, and latency. Recently, some studies have also proposed using artificial intelligence-based techniques such as reinforcement learning to develop intelligent Medium Access Control (MAC) protocols for IoT devices to efficiently predict wakeup schedules and adaptive sleep cycle management to save energy [134].

C. ENERGY-AWARE ROUTING

Wearable devices often connect to other wearables or mobile devices in their surroundings to communicate with the remote instance (either an edge/fog node or a cloud [135]) through the gateway node. It is applicable mostly in healthcare applications where multiple wearable devices coordinate to monitor a patient's overall health condition by communicating data to a common data collection point to be further transmitted to a remote medical facility for further processing and analysis [136]. In this regard, energy-aware routing, i.e., the use of energy-efficient routing protocols in order to prolong the resource-constrained devices lifetime., plays an important role to conserve the energy of network nodes that may otherwise engage in excessive relaying, thus resulting in early battery depletion [137].

Although energy-aware routing seems to be an efficient approach, some overheads are involved in determining the best routing path [138]. Nodes need to be aware of their neighboring nodes' remaining energy levels, which also requires communicating some periodic control messages to share the available resources. Therefore, it is crucial to consider trade-offs while designing an energy-aware routing approach.

D. LOW-POWER HARDWARE DESIGN

With the advancements in electronic equipment design, several units supporting the low -power computing, communication, and sensor s have been developed for future wearables for extended battery life [139], [140], thus, forming a concept of low-power hardware design. Additionally, several prototypes have been developed with low power and miniaturized Application-Specific Integrated Circuit (ASIC) hardware design architectures [141]–[143].

In many wireless devices, the communication subunit is usually considered the most energy-consuming entity [144]. It has been observed that even with duty cycling techniques, a considerable amount of energy is spent listening to the wireless channel for incoming messages and minimizing the chances of collision with other parallel transmissions [145]. Moreover, in highly dynamic and crowded situations where wearable devices need to sense nearby devices for possible data exchanges continuously, the radio needs to be in the listening mode most of the time, leaving little space for duty cycling [146].

Therefore, some studies propose the use of additional near-zero power consumption hardware units called the wakeup radios [147]. These devices are mainly used to listen for any activity over the wireless channel to wakeup the main radio unit as and when needed. These devices are found to be highly energy-efficient. However, the downside is the added cost and space for integrating these wakeup radios and the actual communication units on wearable devices.

E. LOW-POWER COMMUNICATIONS

Most of the wearables available today deploy short-range wireless communication technologies such as BLE [148], Zigbee [149], Wi-Fi [150] despite others. However, the choice of communication technology highly depends on the nature of the application, e.g., if the targeted application requires a high data rate, then Wi-Fi is an optimal choice. Otherwise, using high data rates and high power communication protocols can be inefficient since many IoWT applications do not require it [151].

Generally, low power short-range communications are specifically designed to decrease the power overheads related to data transmission, the technology such as BLE and Zigbee have emerged to be more effective in energy consumption [129], [152], [153]. Furthermore, the advent of low power long-range non-cellular technologies such as LoRa [154], Sigfox [155], and IEEE 802.11ah [156] also appear to be promising candidates for low power wearable devices. However, the industrial gap keeps the cellular technologies (Long-Term Evolution (LTE) for Machine-Type Communications (LTE-M) and Narrowband IoT (NB-IoT)) in their infancy from wearable perspective [157].

F. ADAPTIVE TRANSMISSION POWER CONTROL

Data transmission is often considered the most power-consuming task for wearables, i.e., transmitting a single bit may roughly require 1,000 times more energy than a single computation [158]. Wearables deploy onboard transceiver units that are usually tuned to perform data transmission with a fixed high transmission power to provide transmission coverage in a specific area [159]. However, there can be several arrangements where a comparatively lower transmission power can serve the purpose and effectively communicate the data to a node in close proximity by ineffectively selection the transmission power based on the surrounding environment situation, thus, employing the adaptive transmission power control strategies.

For transmit-intensive applications that involve frequent data transmissions, this problem becomes even more severe. Therefore, always using a fixed high power for data transmissions is inefficient, and an adaptive transmission power control mechanism can prove to be very efficient in terms of energy consumption [160]–[162]. However, the transmitting node needs to know the receiver's relative distance to estimate the amount of transmission power necessary. It may require the exchange of some periodic control messages among nodes if they are not fixed. Recently, some studies have also proposed the use of lightweight ML-based intelligent transmission power control schemes, where nodes iteratively learn their remaining energy levels and adaptively tune their transmission powers to ensure minimum energy consumption while also maintaining a minimum packet error rate [163].

G. COMPRESSIVE SENSING

Compressive sensing is a signal acquisition and reconstruction technique where signal sparsity is exploited to achieve efficiency in energy consumption, bandwidth, and performance [164], [165]. It allows an optimal reconstruction of the actual signal by using significantly fewer samples than required by the Nyquist criteria. Several studies have shown the benefits of compressive sensing in power consumption optimization [165]–[167]. Many wearable applications, such as healthcare, etc., also rely on sparse signals. Therefore, following the Nyquist criteria deploying fixed sensing intervals for sensors embedded in wearables might prove to be inefficient for application involving sparse signals. However, the downside is that this technique can only be used for sparse signals.

In contrast, many other applications would still require higher sampling rates to reconstruct the desired signal at the destination effectively. Some studies advocate using adaptive compressed sensing for applications where the nature of the generated signal is unknown. For example, several activity recognition applications might waste energy in fixed periodic sampling when there is no activity. Therefore, in such cases, adaptive compressed sensing proves to be very effective where sampling rates are varied dynamically as and when required to conserve energy [57]. Furthermore, secure compressive sensing is also used in wireless communications as a cryptosystem with the measurement matrix as a key to secure data exchange between communicating entities [168]. Moreover, it has also gained much attention to the cognitive radio communication field [169].

H. DATA COMPRESSION

Data generation and processing is one of the primary tasks of any wearable device [170]. However, many sense-intensive applications such as healthcare and activity recognition involve continuous sensing and generate vast amounts of data that might be correlated, redundant, or not efficient in some scenarios. Therefore, efficient data compression can be beneficial in several ways and improve the overall performance of the device [171]. Efficiently handling the generated data and discarding redundant and unnecessary data items reduces the data size and processing time while enhancing the device battery life [172].

Hence, data compression techniques have been used in numerous works to reduce the size of the data set that needs to be processed and exchanged to achieve energy efficiency at both computation and communication phases [173]–[175]. Most of the proposed data compression algorithms attempt to enhance the compression ratio that can be interpreted as the degree to which the redundant data is removed while maintaining a particular Root Mean Square Error (RMSE) and SNR are essential considerations in the IoWT applications [55].

I. APPROXIMATE COMPUTING

Approximate computing, i.e., approaches when the calculations do not provide the precise result but rather rely on ‘‘good enough’’ answers quickly, at scale, and with energy efficiency, has emerged as an efficient technique to boost performance and energy efficiency in resource-constrained devices such as wearables [176]. Since many applications in the IoWT rely on redundant and noisy data, approximate computing allows trading accuracy for energy and performance gains [177]. Several applications involving ML, signal processing, image processing, big data analytics, etc., may not require highly accurate results. Instead, findings that are ‘‘good enough’’ might serve the purpose [178].

However, approximate computing’s main challenges lie in identifying the threshold for the minimum required accuracy for any specific application, finding the approximable tasks in the execution flow, and monitoring the application results [179]. Therefore, careful tuning of the approximation techniques can help to achieve optimal performance gains such as execution speed, execution time, latency, and energy efficiency.

J. SECURITY PRIMITIVES-RELATED ASPECTS

Most of the modern wearable devices rely on conventional information security primitives that were not designed with energy efficiency of resource-constrained devices in mind. Today, the developers and researchers have been investigating the aspects of information security enablers suitable for wearable technology, which is especially important for medical and industrial segments. The authors of [180] have investigated the executability of various primitives used in symmetric and asymmetric cryptography, block ciphers, ecliptic-curve cryptography, and conventional hashing functions. The set of measurements has shown that the use of broadly adopted techniques brings significant computational load on wearables compared to, e.g., smartphones. However, the authors did not provide any metrics that could be directly projected on energy efficiency but rather the primitives execution time comparison. As one of the solutions, this work highlights the need to develop specific lightweight primitives keeping in mind the trade-off between energy consumption and security as one of the drivers for efficient resource-constrained devices.

The work presented in [181], [182] outlines a sophisticated scenario of the blockchain systems migration towards wearable devices as an unavoidable step of the distributed systems’ evolution. The authors have developed a testbed allowing to measure the self-discharge rate of the battery of the device caused by the execution of different consensus algorithms. It was proven that Bitcoin-like systems, based on the Proof-of-Work (PoW) consensus [183], are not suitable for battery-powered devices since their operational time decreases almost twice. The authors stress that new consensus mechanisms should be developed and utilized for wearables to reduce the impact of cryptography primitives execution on battery life. One of the discussed solutions for that challenge is the Proof-of-Activity (PoA) algorithm that allows us to step aside from the computational-hungry PoW to a simpler verification procedure executed on the wearable side [184].

The authors of [185] have analyzed the utilization of Hypertext Transfer Protocol (HTTP) vs. Secure Hypertext Transfer Protocol (HTTPS) traffic on personal handheld devices to evaluate the state-of-the-art readiness of wearables for encrypted traffic processing. As an important finding, it was shown that the energy consumption of mobile phones and smart wearables caused by traffic encryption is comparable. In contrast, the leading cause of energy consumption was the communications side and the need for an intermediary gateway. The authors of [186] also elaborate on the need to consider the memory and CPU requirements in order to optimize the executability of cryptographic components better, including the hardware acceleration. Moreover, the work [187] highlights the optimization problem of a power-performance application-oriented solution for wearable motion sensors.

Since wearable themselves are commonly market-available devices without an open-source operating system, with only a few examples opposing this trend [186], the development and integration of novel energy-efficient security solutions are still in their infancy. At the same time, most of the smaller developers do not pay much attention to energy-efficiency aspects.

K. SECTION SUMMARY

This section presented a detailed and comprehensive analysis of the most commonly used strategies to enhance energy efficiency in the IoWT domain. Several challenges and trade-offs were highlighted under each strategy to be considered by the research community while designing novel energy-efficient techniques (more details on challenges are available in the next section). We believe that several strategies can be combined for maximum energy gains and optimal performance for designing power-efficient future wearables.

The next section provides a detailed discussion on the main challenges and future research directions, specifically regarding energy efficiency in wearables. Moreover, we also provide some general challenges and limitations to be taken into account during the the future wearables design.

V. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Wearable technology is already pacing its way towards mass adoption. Numerous aspects limit this evolutionary trend besides energy consumption related aspects that we would like to highlight before concluding the paper. This section continues the discussion on energy-efficiency aspects of wearables by outlining the main challenges and future perspectives of wearable devices from the energy efficiency/power consumption perspective. It provides a summary based on the systematic literature review and extends it with future research directions in this domain.

Table 10 highlights the main identified challenges and proposed mitigation solutions found in the literature. We divide those into five subgroups based on the specifics of the challenge, namely, Architecture (aspects related to physical and logical placement of the node in the network), Networking (algorithms, protocols, and routing aspects), Data Processing (including data storage), and, more generally, Hardware and Software.

The major challenges identified include transmission overheads, wireless technology-related issues, inefficient routing, security-related aspects, processing limitations, storage limitations, lack of hardware acceleration, inefficient use of energy-consuming modules, and battery limitations. The weighted relations between those before-listed groups of challenges are depicted in Fig. 10.

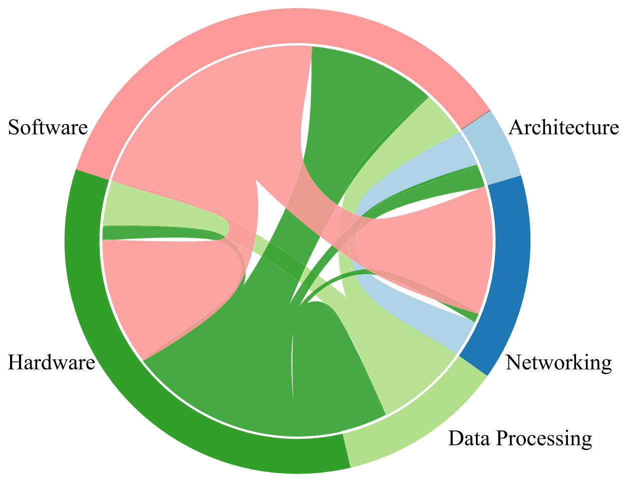

FIGURE 10. Weighted relation between the main energy-efficiency challenge groups.

Besides challenges and with the advancement in the processing units and the demand for high-end wearables relying on heavy computations, the currently available battery power resources might not be enough for the extended device operation. Therefore, it is predicted that energy harvesting will be an essential part of the high power future wearables [188]. Many researchers already work on various opportunities to enable this feature, including microkinetic energy harvesting systems utilizing frequencies occurring in human motion to harvest energy [189], powering wearables with solar energy harvesting [190], self-powering smart fabric [191] and wireless power transfer for implantables [192], [193]. Considering the increasing power requirement of the IoT devices, some researchers have proposed green energy harvesting solutions for IoT devices [194]. However, energy harvesting techniques have not yet been mature enough to be integrated into the IoWT for several reasons. First, the energy harvesting efficiencies of the state-of-the-art energy harvesters are not

TABLE 10. Summary of the main challenges related to energy efficiency of wearables.

Challenge	Groups	Refs.	Observed existing approach
Transmission overheads	A, N	[47]	Embedded signal processing to avoid unnecessary data transmission by carrying out local processing
		[54], [57], [58], [87]	Compressive sensing to avoid generating unnecessary redundant data
		[53], [84], [92], [99]	Embedded ML to carry out complex computation tasks on the device to reduce latency
Wireless technology-related issues	A, HW	[45]	Duty cycling to periodically power off communication modules when not in use to conserve energy
		[49], [61]	Adaptive transmission power control of transceiver based on distance to remote node
		[59]	Use of low power wireless communication protcols such as 6LoWPAN
		[61]	A multi channel TDMA approach to allocate slots for simultaneous transmission
		[109]	An adaptive connection interval selection in dynamic channel environments for improved connectivity
		[98], [148]	Low power wireless communication protocols
Inefficient routing	A, N, SW	[46], [111]	Energy awareness regarding neighboring nodes to select the optimal route
		[50]	Multi parameter cost function for the next hop selection
		[60]	Selective data routing based on the data priority
Security-related aspects	HW, DP, SW	[110]	Content agnostic privacy and encryption protocol eliminating the need for asymmetric encryption
		[180], [181]	Integration of lightweight cryptography solutions including more appropriate elliptic curve types or algorithm implementations
		[186]	More efficient utilization of manufacturer-provide SoCs accelerated for cryptographic primitives execution
		[187]	Finding trade-offs between the primitive and required level of the provided security
Processing limitations	HW, DP, SW	[54]	The use of heterogeneous multicore processor gateway as compared to little cores gateway working as a router
		[64], [86], [104], [105]	Task offloading to leverage high computing resources of nearby devices for improved performance
		[106]	Edge/fog/cloud computing techniques for optimal performance
		[107]	Seamless resource sharing between heterogeneous mobile devices
Storage limitations	HW	[47], [55]	Data compression to reduce the size of the dataset for efficient data processing and storage
		[106]	Edge/Fog/Cloud computing techniques for better performance
		[173]	Data summarization and aggregation
Lack of hardware acceleration	HW, SW	[47], [55]	Data compression to reduce the size of the data set for more efficient data processing and storage
		[64], [86], [104], [105]	Task offloading to leverage high computing resources of the nearby devices for the improved performance
		[186]	Identifying and use of present hardware acceleration, which may not be accessible by the default
Inefficient use of energy consuming modules	HW, SW	[62]	Configurable data acquisition modules
		[88]	Replacing high power consumption modules with low power alternates, e.g., using two accelerometers instead of a gyroscope as a low power alternative for activity recognition
		[83]	An adaptive sampling and powering down sensing modules such as an accelerometer for low intensity user activity recognition
		[108]	Coupling transceiver module with near zero power wakeup radios
Battery limitations	HW, SW	[98]	Applying energy harvesting techniques to gather energy from ambient sources to intermittently charge the battery to enhance its lifetime
		[90], [95]	Low power and low complexity SoC hardware design
		[103]	Efficient computing techniques, e.g., approximate computing

A – Architecture N – Networking DP – Data Processing
HW – Hardware specific SW – Software specific

high enough to independently power wearable devices in the IoWT. Second, the availability of ambient energy is not always guaranteed. Third, the desired miniature design of the wearable devices imposes another challenge since energy harvesting requires integrating multiple additional hardware equipment such as ambient energy harvesters, additional batteries to harvest energy, etc. Therefore, a significant amount of research is required to enable future IoWT devices to continuously generate power from ambient sources to charge their batteries for an extended battery life [195], [196].

From the communications perspective, most of the existing wearable devices connect to the Internet via gateway node (commonly, a smartphone) due to the lack of direct long-range connectivity capabilities [197]. Such a setup can cause significant performance degradation to the high-end wearables that demand high-data rates, e.g., AR/VR/MR or XR applications [198]. Therefore, direct Internet connectivity-enabled devices equipped with IEEE 802.11 or cellular modules are expected to get more attention in the nearest future [199]. Moreover, some other long-range non-cellular connectivity solutions such as NB-IoT, LoRa, Sigfox, etc., are also expected to enter the wearables industry, opening directions for many new wearable IoT applications [200]. Therefore, it is essential for the research community to follow and address the associated challenges such as the impact on the communication channel, reliability, security, privacy, etc.

Moreover, direct Internet connectivity might introduce new challenges in terms of energy efficiency of wearable devices; since communicating directly to an access point (in case of Wi-Fi) or a base station (in case of cellular or non-cellular connectivity) will involve communication at a comparatively longer distance as compared to accessing the Internet through a smartphone/gateway node. Consequently, resulting in high power consumption [23]. Therefore, the use of adaptive transmission power control along with efficient duty cycling and energy harvesting mechanisms will become essential to conserve energy. Additionally, near-zero power consumption wake-up radios to minimize the actual communication unit's energy consumption can also be beneficial [147].

Generally, most of the available wearables are standalone devices in terms of their operation, i.e., multiple wearables are not collaborating towards a common goal rather than fulfill their tasks. However, with the increasing interest of the consumer community in adopting wearables for their day to day tasks, it is expected that individuals will be carrying multiple wearables in their daily routine in the nearest future [15]. Thus, a network of wearables could be formed where personal wearable could benefit from sensing, computing, and transmission resources of other wearables nearby to efficiently carry out the desired tasks through collaboration and forming personal wearable clouds [201].

From the medical domain perspective, consumer wearable devices started to attract more attention to the development of medical area [202]. Some standalone wearable equipment was utilized for patients admitted to hospitals to monitor their health [203]. However, the recent developments including the COVID-19 pandemic [204], have diverted the research attention towards using technology to find a cure and/or disease prevention. Smart wearable technology can be a potential game-changer in the era of COVID-19, where wearables can be used that could notify users of the possible COVID-19 viruses around them. Additionally, wearables can be utilized for contact-tracing purposes to track the potential carriers of airborne infectious diseases, who came in close contact with an upper-tract-disease infected patient to prevent the spread [205]. Importantly, such medical devices and gadgets must have sufficient resources to at least accommodate the user for one whole day [206]. Therefore, the use of low power technologies in the design of future medical wearables is a must [207].

Importantly to note, security and privacy have become critical concerns, primarily due to the medical applications. Wearable devices are often carrying sensitive and private data associated with the users that can be exploited to identify and track individuals. For instance, we observe different device locking mechanisms in wearables, including fingerprinting and facial recognition techniques. Such specific biometry-related data associated with users is the most sensitive information since passwords can be changed while most of biometry or behaviour factors remain unchanged over life of an individual [208]. It has been observed that most commercially available wearables often have very minimal or no security features due to performance degradation issues since many of the available data encryption and security techniques are compute-intensive for wearables [180]. Therefore, the development of lightweight and efficient security and privacy techniques tailored explicitly for wearables is an up-and-coming research area [209].

From the computing perspective, due to the miniaturization of electronic equipment, future wearables are expected to be equipped with more powerful processors with substantial storage resources that will consume much energy if not appropriately handled [210]. Additionally, the increasing demand for high computing resources from diverse wearable applications demands the development of efficient computing techniques that could satisfy not only application requirements but also conserve energy. In this regard, approximate computing or inexact computing have recently emerged as an effective technique where output accuracy is traded for computing time and energy by relying on nearly accurate results [211] (for a detailed discussion on approximate computing refer to Section IV-I.) Similarly, developing in-device signal processing and embedded ML techniques specifically designed for wearables has gained significant attention from the research community [212]. Most wearables are usually recording and communicating raw data to edge devices or remote cloud servers to be analyzed and processed for meaningful information extraction. This behavior not only continuously engages the device's radio, which significantly impacts the battery life of the device but also results in overburdening the limited storage capacity of wearables [213].

On the contrary, if this raw data is processed on the device, the extracted information will consume significantly fewer resources, thus, boosting the device's energy efficiency. For instance, wearables often communicate raw data to remote cloud servers for feature extraction and classification to predict any patient anomaly and/or emergency condition in healthcare applications. It involves not only high latency but also consumes high energy due to continuous data transmissions. Therefore, on-board lightweight embedded ML techniques could improve the battery lifetime of wearables many folds while enhancing device performance [214].

Next, comfort and ease of use are vital for wearables. Since these devices remain in close contact with the human body and skin, it is vital to consider those while developing future wearables and, especially, to take into account their chances of overheating or short circuit. Some of the high-end wearables available today dissipate much heat and they may not get wide acceptance by the consumers due to that reason. Therefore, those are also essential considerations to be taken care of in the development of future wearables.

In its entirety, modern wearable devices as part of the general Information Technology (IT) ecosystem can also help make other systems more energy-efficient. A recent study projected that IT-enabled devices could cut global greenhouse gas emissions by 16.5% in 2020 [215]. The gains will be achieved through many different applications, ranging from smart power grids, sophisticated communications systems to sensor-driven intelligent traffic management, and more keeping the wearables as part of the general environmental picture.

VI. SYSTEMATIC REVIEW SUMMARY

The need to develop highly energy-efficient solutions has increased manifold with the advances in wearable technology and the increasing interest of users towards wearables for a wide range of value-added and entertainment applications. Moreover, charging personal devices and electronic gadgets more frequently is highly unpleasant and inconvenient from a user's perspective. Therefore, energy efficiency in wearables has become an active research area. Although more sophisticated and efficient batteries have been developed for an increased battery life of devices, the need for enhanced processing power and complexity of applications is also rising at a significant pace. Therefore, the design of highly energy-efficient solutions has become necessary to fulfill the requirements of the latest power-hungry wearable sensors and applications to satisfy user demands.

In this paper, we presented a systematic literature review of the state-of-the-art research papers in the area focusing on the energy-efficiency aspect in the IoWT domain. We presented a taxonomy of the IoWT solutions from an energy efficiency perspective based on the targeted application area classifying them into four categories, namely healthcare, activity recognition, smart environments, and general solutions. It was observed that most of the existing solutions target healthcare-related applications because wearables were historically developed for specific medical purposes. However, more recently, with the advancements in the field, wearables have found applications in many diverse fields apart from healthcare. Additionally, a statistical analysis of the available solutions was presented in terms of year-wise publications revealing an increasing trend in the research related to wearables, and we anticipate it to increase further in the coming years.

Further, a detailed discussion based on the qualitative and comparative analysis of existing studies in each category was provided, presenting their advantages, limitations, main performance parameters, and major contributions, as well as giving a quick overview of this field's research. Similarly, a statistical analysis was presented to depict the percentage of tools used in the performance evaluation of the proposed solutions, which revealed that the research community is more inclined to develop a prototype to validate the efficiency of their proposed solution. However, some studies presented simulation-based results only where MATLAB was found to be the most widely used simulator besides others. Whereas, some fraction of the studies presented both simulation-based results validated through real-time experiments on prototypes. Similarly, a statistical analysis was presented showing BLE to be the most widely used mainly due to its low power consumption feature to present another vital insight related to the most commonly used communication technologies in wearables today. Moreover, to facilitate new researchers in the field, a summarizing discussion was presented on the main techniques adopted in the literature to enhance wearables' energy efficiency highlighting the trade-offs involved.

Although, the solutions addressing various aspects in the IoWT domain already exist, we believe the field is far from saturated. We foresee that there is still room for improvement and further research. Therefore, we investigated open research directions in the field to motivate researchers for developing future energy-efficient IoWT-based systems.

LIST OF ACRONYMS

3D	Three Dimensional
AR	Augmented Reality
ASIC	Application-Specific Integrated Circuit
BAN	Body Area Network
BLE	Bluetooth Low Energy
CNN	Convolutional Neural Network
CPS	Cyber-Physical System
ECG	Electrocardiography
EEG	Electroencephalography
EMG	Electromyography
GMG	Global Greenhouse Gas
GSR	Galvanic Skin Response
HTTP	Hypertext Transfer Protocol
HTTPS	Secure Hypertext Transfer Protocol
HVAC	Heating, Ventilation, and Air Conditioning
ICT	Information and Communications Technology
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
IoWT	Interent of Wearable Things
IT	Information Technology
KM	Kuhn-Munkras algorithm
KPI	Key Performance Indicator
LTE	Long-Term Evolution
M2M	Machine-to-Machine
MAC	Medium Access Control
MANET	Mobile Ad Hoc Network
MCC	Mobile Cloud Computing
MCSS	Multicombined Computing Sorting Segmentation
MEC	Mobile Edge Computing
MEMS	Miniature Micro-Electro-Mechanical
MR	Mixed Reality
ML	Machine Llearning
NB-IoT	Narrowband IoT
PoA	Proof-of-Activity
PoW	Proof-of-Work
PPG	Photoplethysmography
QoS	Quality-of-Service
RFID	Radio-Frequency Identification
RMSE	Root Mean Square Error
SNR	Signal to Noise Ratio

SoC	System on Chip
SK	Skin temperature
TDMA	Time-Division Multiple Access
WBAN	Wireless Body Area Network
WBSN	Wearable Body Sensor Network
WIoT	Wearable Internet of Things
VR	Virtual Reality
Wi-Fi	Wireless Fidelity
XR	Extended Reality

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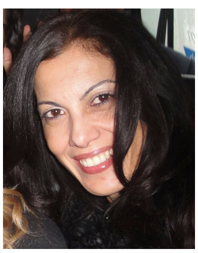

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