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Review

Requirements for Energy-Harvesting-Driven Edge Devices Using Task-Offloading Approaches

Meriam Ben Ammar [1,2,3,*], Imed Ben Dhaou [4,5,6], Dhouha El Houssaini [1], Salwa Sahnoun [2,3], Ahmed Fakhfakh [2,3] and Olfa Kanoun [1]

1. Measurements and Sensor Technology, Faculty of Electrical Engineering and Information Technology, Chemnitz University of Technology, W206, 09126 Chemnitz, Germany; dhouha.el-houssaini@etit.tu-chemnitz.de (D.E.H.); Olfa.Kanoun@etit.tu-chemnitz.de (O.K.)
2. National School of Electronics and Telecommunications of Sfax, University of Sfax, Sfax 3018, Tunisia; salwa.sahnoun@enetcom.usf.tn (S.S.); ahmed.fakhfakh@enetcom.usf.tn (A.F.)
3. Laboratory of Signals, Systems, Artificial Intelligence and Networks, Digital Research Center of Sfax, University of Sfax, Sfax 3038, Tunisia
4. Department of Computer Science, Hekma School of Engineering, Computing and Informatics, Dar Al-Hekma University, Jeddah 22246-4872, Saudi Arabia; imed.bendhaou@utu.fi
5. Department of Computing, University of Turku, FI-20014 Turku, Finland
6. Department of Technology, Higher Institute of Computer Sciences and Mathematics, University of Monastir, Monastir 5000, Tunisia

* Correspondence: meriam.ben-ammar@etit.tu-chemnitz.de

Abstract: Energy limitations remain a key concern in the development of Internet of Medical Things (IoMT) devices since most of them have limited energy sources, mainly from batteries. Therefore, providing a sustainable and autonomous power supply is essential as it allows continuous energy sensing, flexible positioning, less human intervention, and easy maintenance. In the last few years, extensive investigations have been conducted to develop energy-autonomous systems for the IoMT by implementing energy-harvesting (EH) technologies as a feasible and economically practical alternative to batteries. To this end, various EH-solutions have been developed for wearables to enhance power extraction efficiency, such as integrating resonant energy extraction circuits such as SSHI, S-SSHI, and P-SSHI connected to common energy-storage units to maintain a stable output for charge loads. These circuits enable an increase in the harvested power by 174% compared to the SEH circuit. Although IoMT devices are becoming increasingly powerful and more affordable, some tasks, such as machine-learning algorithms, still require intensive computational resources, leading to higher energy consumption. Offloading computing-intensive tasks from resource-limited user devices to resource-rich fog or cloud layers can effectively address these issues and manage energy consumption. Reinforcement learning, in particular, employs the Q-algorithm, which is an efficient technique for hardware implementation, as well as offloading tasks from wearables to edge devices. For example, the lowest reported power consumption using FPGA technology is 37 mW. Furthermore, the communication cost from wearables to fog devices should not offset the energy savings gained from task migration. This paper provides a comprehensive review of joint energy-harvesting technologies and computation-offloading strategies for the IoMT. Moreover, power supply strategies for wearables, energy-storage techniques, and hardware implementation of the task migration were provided.

Keywords: energy harvesting; IoMT devices; energy autonomous; wearables; energy-storage; energy management; fog edge computing; task offloading; deep learning; reinforced learning; IoMT

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1. Introduction

With the spread of Internet of Medical Things (IoMT) applications, more intelligent services are presently emerging in the healthcare and medical areas, such as remote patient monitoring [1,2], telemedicine [3], biometrics scanners [4] and vital signs monitoring [5,6].

In general, the IoMT comprises different and heterogeneous smart devices, such as wearables, wireless sensors, and medical monitors, which can be applied to the human body, at home or in hospitals to provide better and more efficient remote monitoring. By combining information technology with medical information, wearable devices can perform better monitoring of medical and healthcare applications, resulting in reduced complexity and enhanced efficiency. With the use of the IoMT, physicians and healthcare responsible are also able to access different and real-time medical databases, which ensures a better understanding and identification of their patients' health issues.

The IoMT presents an application of the Internet of Things (IoT) in the field of medical and healthcare. The IoT comprises physical network devices equipped with sensors, software, and network connections that facilitate data collection and transmission. It can integrate cloud services and fog centers, where complex and efficient data processing is carried out with high processing capabilities. Considering the basic concepts of the IoT, the general layer architecture of IoMT is illustrated in Figure 1. It comprises four main layers, namely the sensing layer, the edge layer, the fog layer and the cloud layer. In the sensing layer, the wireless sensors and medical devices are installed along with different actuators. They are responsible for sensing medical and physiological information, and executing specific controlling and monitoring requests such as laser positioning and equipment maintenance. The raw data collected from the end devices are collected and transmitted to the edge devices, where data processing, reduction and analysis are carried out. Devices with edge computing processors provide improved security while operating at a low power level. Within the fog layer, local area networks are installed, where the data are transmitted from endpoints to a gateway, where it is then transmitted to sources for processing and return transmission. By the end, data are transmitted to the cloud layer, which can access several IoT devices at the same time. It permits real-time and continuous data processing with higher computational capabilities. However, even though wearable devices are becoming more powerful and affordable, machine-learning-based tasks that typically require more computation resources may overload them with higher data communications and, therefore, higher energy consumption.

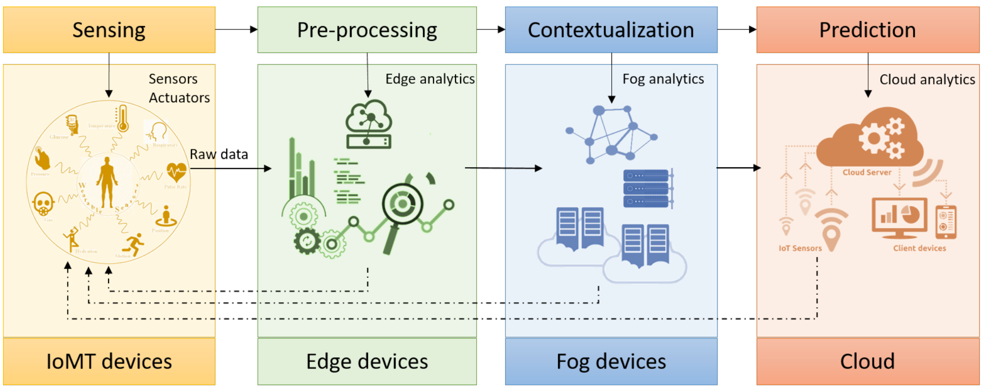

Figure 1. General layers architecture of IoMT system.

Therefore, it becomes imperative to offload some tasks from resource-constrained edge devices to co-located edge devices, such as the fog. Applications that require intensive computation resources are often offloaded to cloud servers to be processed, which improves IoT device capabilities. Cloud computing, by contrast, may cause high latency response times, privacy and security issues. As a solution, some studies proposed to offload tasks to a Mobile Edge Computing (MEC) server via edge devices that can be placed near end devices and process some computational capacity. Thus, transmission latencies are reduced, and reliability and security are enhanced. Even though computation offloading over fog edge computing or MEC has reduced the energy consumption of IoMT devices to a certain degree, their energy limitations remain a key concern. However, most devices are powered by batteries, which limits their energy resources and operating times. Similarly, computation performance may be affected if not enough battery energy is available for task transmission. A larger battery or more frequent recharging can address this problem. In contrast, the small size of IoMT devices makes it difficult to equip them with larger batteries or to recharge their batteries frequently. To address these challenges, energy-harvesting technologies have been identified as promising techniques to increase battery life and achieve energy-autonomous systems. Figure 2 shows the general architecture of an IoMT system with the integration of EH-supplied systems and considering the task-offloading aspect. The IoMT system includes various types of sensors used, most likely activity sensors (presented in red circles in Figure 2), physiological sensors (presented in green circles in Figure 2). Sensor are placed over the human body within a network, where each sensor is responsible for monitoring certain physical information. The sensor data are gathered in the base station to be transmitted to the next IoT layer, which can be either an access point, a gateway or a mobile device. Later, the collected data are transported to the fog layer and then the cloud. Communication can be established between different installed devices over the different layers. During the communication, information related to the actual status of the corresponding devices, such as the residual energy level, neighbor list and reception acknowledgement could be shared. This information care is used later to decide upon the most appropriate device for task offloading. Offloading involves sharing details about which device will be best suited to execute the current task, the type of task that will be executed, and how it will be executed. Task offloading can occur at different levels of the IoMT system, such as from the WBAN to the gateway and from the gateway to the fog, to the cloud.

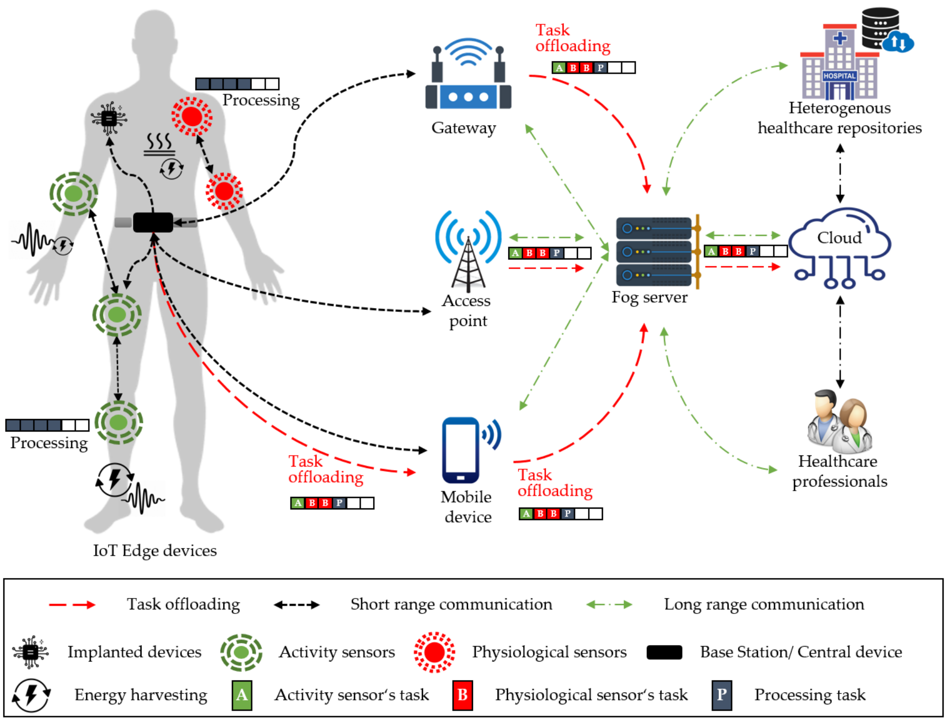

Figure 2. General architecture of an IoMT system based on energy harvesting and with consideration of task offloading.

Within the framework of IoT for medical applications, continuous data transmission takes place over the different layers of the network. Therefore, different sensor and communication technologies are used for sensing and transmitting data in real time, enabling fast calculations and optimal decision-making. It is crucial to satisfy the trade-off between the energy consumption, computational capability and data transmission for a real-time and accurate operation. Several schemes for energy efficiency and management are required to respond to these challenges. In general they can be classified into four main categories:

- Resources allocation ensures a better allocation and management of the available resources, mainly radio and energy resources.
- Energy harvesting and transfer provide a sustainable energy supply, which are harvested from ambient resources. In the case of wearable systems, the energy can even be harvested from the human activities, such as breathing and movement.
- Hardware systems are explored during the development and design of wireless nodes and devices with consideration of the minimum energy consumption.
- Network installation enables the definition of appropriate infrastructures that maximize energy efficiency and ensure the data transmission and computational capabilities.

In this direction, it is important to investigate energy-efficient solutions for IoMT system, where intensive tasks and data processing are realized in a strict execution time. In particular, the communication and data transmissions need more attention, especially in the case of limited energy sources and computation capabilities. In this direction, investigations into energy-harvesting solutions along with task-offloading concepts present a promising solution to deal with excessive demands for a stable communication and data transmission. The contributions of this paper are:

- We provide a literature review of the state-of-the-art joint energy-harvesting and task-offloading approaches in fog edge computing systems.
- We compare the state-of-the-art related surveys based on specific key features.
- We investigate energy-harvesting technologies and energy-storage strategies for IoMT devices.
- We survey recent research efforts on task offloading in fog edge computing and related design considerations.
- We review existing approaches for the design of patient-centered care system.

The paper is organized as follows. Section 2 surveys research efforts related to joint energy harvesting and task-offloading approaches in fog edge computing systems. Section 3 presents the task-offloading approaches for fog edge computing, and deep-reinforcement learning-based algorithms. Section 4 highlights the related design considerations and challenges for EH driven task offloading. Section 5 reviews possibilities of energy supply, energy-storage strategies and recent trends in energy harvesting. Section 6 presents requirements for patient-centered care system. Finally, Section 7 concludes the paper.

2. Related Works

Recently, task offloading in fog edge computing systems has gained considerable attention due to the increasing development of IoMT devices. In [7], the authors developed a deep-learning-based, Internet of Medical Things-enabled edge computing framework for tackling COVID-19. It detects various COVID-19 symptoms and generates reports and alerts for medical decision support. Results indicate that the system can be used to effectively manage in-home health during a pandemic. Nevertheless, improvements to the system accuracy were needed as well as implementations with real subjects. In [8] a joint optimization framework was also proposed for IoT fog computing to achieve optimal resource allocation. The results show that the proposed framework enhanced the performance of IoT-based network systems. In [9] authors investigated delay-sensitive task offloading in edge-enabled healthcare services. A priority-aware service provisioning was proposed, allowing edge server computing resources to handle hard-deadline tasks earlier than soft-deadline tasks which have a lower priority and can tolerate longer delays over hard-deadline tasks. In contrast, the authors plan to examine how hard-deadline tasks can be placed in remote healthcare applications where ensuring high reliability is a crucial requirement.

When focusing on the increasing number of tasks that require high computational capability and consequently more energy, mobile devices need effective mechanisms to figure out which tasks to perform locally and which to migrate to the cloud. The authors in [10] discussed different computational offloading techniques. They consider the offloading either to a fog node or a cloud. They both have their trade-offs. The cloud, as an example, is rich in terms of resources, but offloading computational tasks to cloud servers can lead to security and privacy issues and it is also far away from mobile nodes. In contrast, fog is nearby but has limited resources. Hence, offloading to a cloud or fog consumes different amounts of energy and increases computation performance. In this context, the authors proposed an energy consumption-oriented algorithm to reduce energy consumption when offloading tasks. Initially, they compute the consumed energy when offloading the task to the fog compared to the cloud. Afterwards, they evaluated which entity would be preferred for the task based on the computation requirements. Based on these factors, the task is then offloaded to the desired entity.

Energy harvesting is a promising technology for converting ambient (solar, wind, etc.) and human energy (motion, breath) into electrical power, enabling communication systems to achieve energy-autonomous and efficient communications. In [11] the joint offloading and resource allocation issues in energy harvesting small cell networks is addressed to maximize the number of tasks performed by edge servers while reducing their energy and delay costs. In [12], the authors proposed a deep-reinforcement-learning-based framework for online offloading to reduce the computational complexity in large EH-driven networks. The proposed algorithm can successfully improve offloading behavior by implementing a deep neural network that learns binary offloading decisions based on past offloading experiences. In contrast, a distributed implementation of the proposed algorithm is still needed to enable the users to make offloading decisions in a distributed manner via a learning process. Similarly, a reinforcement-learning-based privacy-aware offloading scheme for a healthcare IoT device supplied by energy harvesting was proposed in [13]. The offloading policy applied on the edge device can be determined by considering the privacy level, energy consumption, and computation latency at each time slot. In [14], the authors investigated computation offloading and resource allocation issues with multiple energy harvesting supplied mobiles. All mobile devices initially harvest energy from RF signals and then use it to perform their own tasks locally or offload them to a MEC server. Some other offloading schemes can also achieve self-sustaining operations. In [15], for instance, the state-of-the-art of methodologies for task offloading in MEC and wireless power transfer to end nodes were recently described. The authors demonstrated the effective use of the Wireless Power Transfer (WPT) technique to charge end mobile phones which have gained more popularity in MEC. However, the increasing demand for computing resources may degrade the performance of MEC. Accordingly, they highlighted the influence of making decisions between task-offloading implementations and offloading locations on the power consumption of MEC devices.

Energy-efficient appliances have become prevalent in various fields and industries, including health care. Therefore, energy management is an effective technique for evaluating the energy efficiency of different devices. By contrast, the surveyed contributions lack discussions of joint energy-harvesting technologies, fog edge computing, and energy management techniques which are vital for IoMT devices.

Table 1 compares the state-of-the-art-related surveys based on specific key features.

Table 1. Comparison between state-of-the-art surveys.

Reference	Fog Edge Computing	Task Offloading	Energy Harvesting	Energy Storage
[16–18]	✓	-	-	-
[19,20]	✓	✓	-	-
This work	✓	✓	✓	✓

3. Principles of Task Offloading

3.1. Pre-IoT Age

Task or computation-offloading theory emerged to respond with the need to speed up task processing in hardware. Task migration in a distributed system aims at balancing the load among available processors without a drastic increase in the communication overhead [21,22]. Two classes of algorithms have been devised: static and dynamic. Communication protocol plays a pivotal role in balancing the load among processors. Three types of control models have been articulated for load balancing: centralized, distributed, and hybrid [23].

In a multicore/multiprocessor system, task offloading has been used to speed up the execution of multitasks, given a process P_1 that can be decomposed into n independent processes, $P1, n$ and M cores. Each process k requires an execution time $t_{k,m}$ on the mth core, such that $m \in \{1, \ldots, M\}$ and $k \in \{1, \ldots, n\}$ (see Appendix A). The energy dissipated by the mth core to run the kth process is $E_{k,m}$. The task offloading seeks an offloading algorithm that assigns tasks such that the execution time is met at the lowest possible energy consumption, i.e., the offloading should solve the following optimization problem.

$$
\begin{aligned}
\min \quad & \sum_{m=1}^{M} \sum_{i=1}^{n} \delta_{i,m} E_{i,m} \\
\text{s.t.} \quad & \sum_{k=1}^{n} t_{k,m} \leq t,, \\
& n \leq M
\end{aligned} \tag{1}
$$

where $\delta_{i,m} \begin{cases} 1 & \text{if } P_i \text{ runs on processor } m \\ 0 & \text{else} \end{cases}$.

The authors of [24] devised an offloading strategy that moves the computationally demanding task from CPU to GPU. They further demonstrated this strategy by considering the implementation of a signature-matching intrusion detection system. This approach has been generalized to cover the multicore architecture with and without accelerators.

Offloading can be used to balance the load among cores or processors in a multiprocessor system. This is often regarded as task migration that aims at moving the task execution from one core/processor using a given performance metric: power consumption, thermal energy, and dark silicon [25]. Communication-driven task migration attempts to migrate tasks to adjacent cores.

3.2. Post IoT Age

The Internet of Things, IoT, is the new trend in connectivity spawned from progress in sensors, embedded systems, and communication technologies. It is a three-tier architecture that is composed of a perception/sensors layer, connectivity layer, and application layer [26].

Mobile edge computing, MEC, is a new frontier in computing technologies. Multitude factors have contributed to the emergence of edge computing. Traditionally, cloud computing has been the dominant technology for the storage and processing of big data. Conventional task-offloading techniques have been proposed to migrate computationally intensive tasks/applications to cloud servers for processing. The offloading decision is aimed at either reducing end-user power consumption or increasing system performance [27]. However, the offloading strategies devised for cloud computing are not adequate in today's technologies for the following reasons: (1) Cloud servers cannot sustain the real-time processing of critical tasks, (2) the growing need for data protection and privacy, (3) the exponential increase in the number of IoT devices, and (4) the rising concern of the power consumption of data centers [28]. It has been reported that in the US, data centers consume up to 2.2% of all utility power [29]. According to the International Energy Agency (IEA), nearly 1% of global energy is consumed by data centers (roughly 250 TWh).

Edge computing, EC, addresses the shortcomings of cloud computing by bringing cloud-like services and operations close to the user. Task-offloading techniques have also been developed for edge computing. Fog computing is a term coined by CISCO and emerged after edge computing [30,31]. Fog-computing architecture, as illustrated in Figure 3, is composed of IoT end devices, fog devices that can perform processing and storage (such as micro cloudlet and gateways), and cloud layer (typically data centers and cloud servers) [32,33].

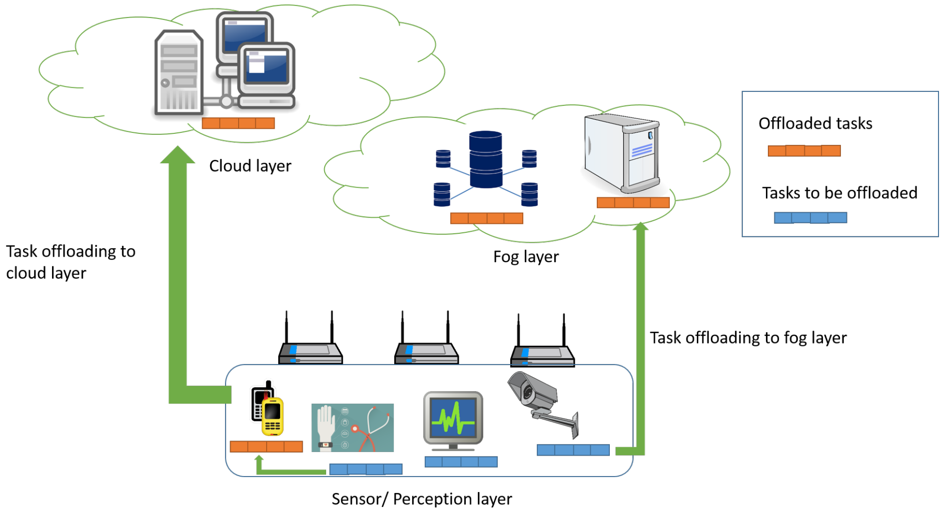

Figure 3. Offloading strategies using fog-computing paradigm. The fog layer is composed of cloudlets (small-scale data centers),and storage (fog servers). The cloud layer houses data centers and servers.

In the realm of the fog-computing paradigm, task offloading has become a hierarchical approach in which an offloading algorithm can execute the task locally using a specialized core, or nearby on an edge device, or remotely on fog or cloud nodes.

Task migration to near or far end nodes needs to account for the cost of the communication protocol: power and delay. In the context of fog computing, the offloading algorithm needs to solve the following optimization algorithm.

$$\begin{aligned} \min \quad & \sum_{m=1}^{M} \sum_{i=1}^{n} \delta_{i,m}(E_{i,m} + EC_{i,m}) \\ \text{s.t.} \quad & \sum_{k=1}^{n} (t_{k,m} + \tau_{k,m}) \leq t, , \\ & n \leq M \end{aligned} \tag{2}$$

where $EC_{i,m}$ is the energy consumed to transmit data of task P_i to processor m, and $\tau_{k,m}$ is the latency to transmit task data to the processor m. Those parameters depend on the type of the communication protocol as well as the load of the remote processor that will execute the task.

3.3. *Offloading Algorithms*

The offloading algorithms aim to find a suitable processor (locally or remotely) to execute a task given a certain constraint. In wearables, offloading can be done at two stages: from wearables to edge devices or from edge device to fog/cloud devices [34]. The offloading device keeps on checking the estimated available power and compares it with the forested power demands. The offloading algorithms are invoked whenever the power demands exceed the available power (harvested and stored) and the energy consumed by the communication unit is less than the energy consumed by task processing. This concept is illustrated in Figure 4. Offloading can be combined with advanced techniques for power management such as sleep, dynamic voltage and frequency scaling (DVFS), and approximated computing [35].

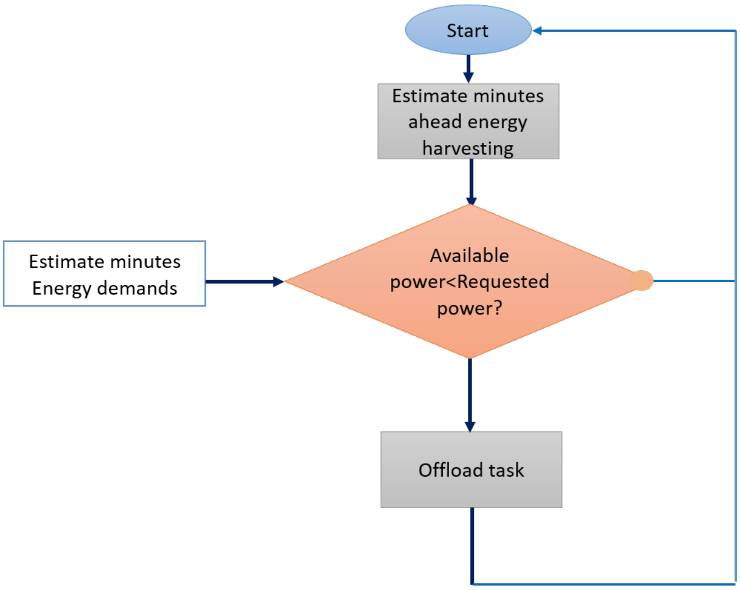

Figure 4. Principles of energy-aware offloading algorithm.

3.3.1. Algorithm Classification

Numerous offloading algorithms for fog computing have recently been proposed. Those algorithms belong to two categories: learning and non-learning. Table 2 summarizes the types of offloading algorithms proposed recently.

Table 2. Recently proposed offloading algorithm.

Reference	Algorithm Type	Optimization Problem	Objective
[36]	Heuristic	Approximation algorithm	Reduce energy consumption of wearables
[37]	Heuristic	Mixed-integer nonlinear programming	Joint scheduling and offloading
[38]	Coalition game theory	merge and split	maxi- mize the total numbers of computed bits
[39]	Evolutionary	genetic algorithm	joint optimization of load balance and propagation delay
[40]	Deterministic	Iterative	balance relays energy
[41]	Reinforcement learning	decentralized partially observable Markov decision process	Maximizing IoT utility and satisfying delay requirements
[42]	Reinforcement learning	Deep Deterministic Policy Gradient	Maximizing task completion rate and reducing task latency
[43,44]	Reinforcement learning	Q-deep learning	Reduce computation latency

3.3.2. Deep-Reinforcement Learning

In recent years, much attention has been given to deep-reinforcement learning (DRL) in task offloading. Reinforcement learning, RL, is a branch of artificial intelligence in which an agent interacts with the environment and learns using two functions: reward and punishment. Punishment is a negative reward. In RL, the learning cycle is not based on a training dataset; instead, the agent interacts with the environments with no prior knowledge and obtains immediate feedback based on its performance. The environment is modeled as a Markovian Decision Process (MDP). In RL an experience is defined as the triple (s_t, a_t, r_t), where s_t, a_t, and r_t are, respectively the state, action and reward at the time

t. The agent determines the action based on a policy, $\pi(s)$. Q-learning algorithm is an offline policy that estimates $\pi(s)$ with guaranteed convergence. The mapping between the policy and the state at a given time t is given by (3) [45]

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha(r_t + \gamma \max_a Q(s_{t+1}, a_t) - Q(s_t, a_t)), \tag{3}$$

where α is the learning rate, and γ is the discount rate. In RL, the agent tends to maximize the rewards. This concept is illustrated in Figure 5.

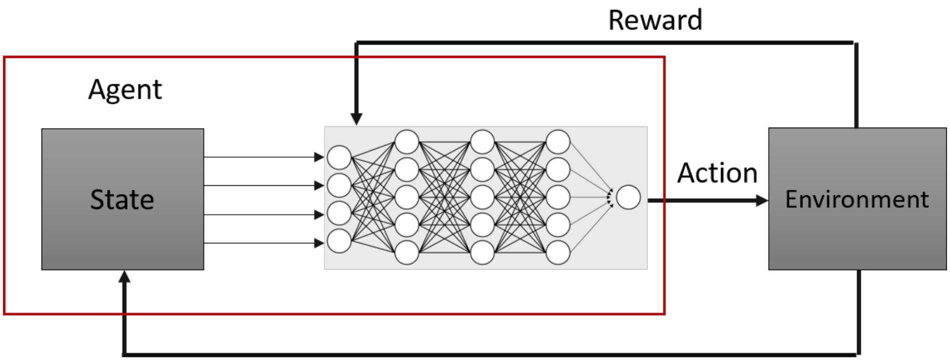

Figure 5. Principles of DRL.

Offloading algorithms-based Q-Learning has been devised in many published reports such [11,43,44,46–48].

In [46], the authors devised a dynamic computation-offloading strategy for an MEC system using Markov decision process theory. The authors considered IoT devices with energy-harvesting techniques. The optimal offloading is achieved using a low-complex after-state learning method.

The problem of task offloading in the context of MEC has been formulated in [47] as a constrained Markov decision process (CMDP). The authors applied Lagrangian primal-dual optimization and devised a deep-reinforcement learning algorithm to solve the relaxed CMDP.

Dynamic computational offloading for MEC systems with EH-enabled IoT devices considering multiple offloading servers has been studied and solved in [48]. The authors elaborated an offloading algorithm using deep Q-learning techniques.

Hardware implementation of the Q-learning algorithm received scant attention. Most of the reported implementation focuses on designing an accelerator using FPGA technology. The lowest power consumption has been reported to be 37 mW for a Q-matrix of dimensions eight states and four policies [49].

The work of [41] considered task offloading with energy harvesting for an IoT MEC system. The offloading problem has been formulated as a decentralized partially observable Markov decision process. They further reduced the computational complexity by searching for an approximated solution using an RL decentralized offloading algorithm. The results, obtained using Matlab simulations, showed that the proposed reduces both average delay and average energy consumption.

To this end, it is crucial to identify the power consumption during different activities of the end devices, in particular data processing, data transmission and communication. In the following section, specific design considerations for task offloading are presented, which may influence the power consumption and the latency of the software and hardware components of the IoMT systems. The main focus is attributed to the choice of the communication protocols for IoT devices with consideration of the energy consumption.

4. Design Considerations for the Task Offloading

With respect to the general architecture of IoMT, Wireless Body Area Networks (WBANs) [38,50,51] are installed where various types of sensors are used, most likely activity sensors (e.g., accelerometer), physiological sensors (e.g., heart rate, ECG and body temperature) and environmental sensors (e.g., humidity and air pressure) (see Figure 1). Various types of applications are recognized with enhanced sensing and communication capability, such as biomedical and wearable solutions for health monitoring, human activities control, organ implantation monitoring and remote surgical interventions. These applications require a high data rate, low latency and high quality of services (QoS) [39,40,52], in order to ensure precise, real-time and secure medical applications. With the integration of the IoMT, it is more challenging to identify the most appropriate strategy that enables efficient handling of the intensive and continuous requests from the installed wireless devices on the human body promptly. Moreover, wireless sensor nodes are battery powered, where the lifetime of the battery is directly dependent of the number of executed tasks along the process. Due to this, it is important to increase the computation capacity of battery-powered devices when performing intensive computing tasks while ensuring real-time intervention and data transmission. In this context, the choice of suitable data transmission and communication protocols has a strong influence on the evaluation of the task-offloading algorithm in terms of processing time, energy consumption and computation. In the following, an overview of the most common communication protocols is provided.

4.1. Communication Protocols

The general architecture of IoMT is reported in Figure 1. The provided architecture is composed of three main layers: (1) the things/devices layer, where the WBAN is installed, along with the gateway devices, (2) the fog layer, and (3) the cloud layer [53,54]. Different communication technologies can be identified within each layer, which enable transmission of the data from the end devices to the end user.

In the first layer, different sensor nodes are installed on the body, which build the WBAN. Sensor nodes can be implantable, wearable or mobile, placed for example in the hand of the patient. In this type of network the communication between sensors is carried out within a short range of 2 to 3 m. These devices, basically, require small power sources with respect to the safety and security of the user. Therefore, with respect to the low power specification and small communication range, the standard Industrial Scientific and Medical (ISM) band is sufficient to cover the installed nodes [55,56]. Various communication technologies are supported in the ISM band, such as ZigBee, Bluetooth and Wi-Fi. Moreover, alternative communication technology is introduced such as the Intra-Body Communication (IBC) technology [57,58]. Through IBC, the human body is used as a transmission medium, enabling power-saving, and thus improving the robustness and security of communications. Due to these advantages, IBC has been included as a third physical layer in the IEEE 802.15.6 standard for wireless body area networks designated as Human Body Communication (HBC) [59]. A central device, refereed also as base station, is responsible for collecting sensor data and forwarding them to the next communication layer. Accordingly, intermediate devices are installed as a bridge between the small interconnected WBAN and the exterior local network, namely the Wireless Local Area Network (WLAN). In this case, local gateways are used such as mobile devices, access points or simple mid-layer gateways. Typically, they provide a bridge between the IoT edge devices and the fog and cloud servers. They enable the passing of data from the discrete sensor network to the other cloud and application layers. On one side, common communication technologies can be initiated between the WBAN' nodes and the intermediate gateways, such as the Wi-Fi and Bluetooth. In the other side, communication with the fog and cloud server can be realized through 5G, Wi-Fi or GPR [60,61]. To this end, data communication and storage are carried out over this layer, whereas in the IoT layer, installed wireless devices are periodically transmitting information. Sensor devices remain awake for a specific time frame from time to time to transmit the required information.

Within the second layer, local servers and gateway devices for the fog network are placed. These devices enable the processing of the collected data. Excessive and complex processing and data-mining algorithms can be carried out at this stage. Later, the collected data are redirected to the cloud layer for further processing. In the case of the cloud or fog layer, more powerful and long-range protocols are required, namely the LoRaWAN, Sigfox, NB-IoT and LTW-M [62], which ensure a better coverage range with a minimum of 1 km in urban deployment and 10 km in rural deployment. Moreover, the fog layer is in connection with healthcare experts responsible, which permits a reduction to the time delay of the interpretation and execution of specific tasks and decisions. In the third layer, powerful data storage and computation resources are installed. In this instance data analysis, decision-making and urgent intervention can be recognized. In addition, the cloud layer permits the incorporation of various and heterogeneous healthcare systems, which enables a real-time and continuous access to the current patient, equipment and planned tasks supervision and monitoring. Basically, this layer consists of cloud-based resources that will store the data generated by the medical infrastructure and be used to perform analytical work as needed in the future [54]. An overview of the common communication technologies used in WBANs is presented in Table 3 [63,64].

Table 3. Comparison between communication technologies used in the WBANs.

Criteria	Range in m	Data Rate	Frequency	Standard	Energy Consumption
Bluetooth [65,66]	<10	1–3 Mbits/s	2.4 GHz	IEEE 802.15.1-	<30 mA
NFC [67]	0.1	424 Kbit/s	13.56 MHz	ISO/IEC 1800-3	<15 mA
RFID [68,69]	<12	100 Mbit/s	LF: 125–135 KHz, HF: 13.56 MHz, UHF: 868–930 MHz, Microwave 2.45, 5.8 GHz,	ISO/IEC 1800	-
BLE [66]	10–300	125 Mbit/s	2.4 GHz	IEE 802.15.1	<15 mA, 10–100 mW
ZigBee [66,70]	10–500	250 Kbit/s	2.4 GHz	IEEE 802.15.4	<16 mA, 10–100 mW
Wi-Fi [64,70]	100	11 Mbit/s	2.4, 5 GHz	IEEE 802.11 a/b/g	-
LoRaWAN [71,72]	∼5 in urban 20 in rural	56 bits/s UL 296 bits/s DL	868, 434, 915 MHz	LPWAN	Sleep: 7.66 µA to 34 mA Tx: 133 mA Rx: 16.3 mA
Sigfox [73,74]	∼10 km in urban ∼40 km in rural	100 bits/s UL 60 bits/s DL	868, 434, 915 MHz	LPWAN, UNB	Sleep: ∼1 µA, Tx: 49 mA Rx: 19 mA
NB-IoT [75–77]	∼1 km in urban ∼10 km in rural	220 Kbits/s	Licensed LTE	LPWAN	Sleep: 13 mW Tx: 716 mW, Rx: 21 mW

4.2. Energy Consumption of Wireless Nodes

Typically, in the task-offloading paradigm, computing tasks are created by end devices (e.g., wireless sensor nodes, central devices). Therefore, the energy requirement at the level of the wireless node, as well as the network, are emphasized. Therefore, characterizing the energy consumption of the end device is crucial to create a balance between the energy requirement, demands and consumption. Essentially, the wireless sensor node is composed of four main units: energy management unit, communication unit, data processing unit and sensing unit. The energy management unit is responsible for converting the energy retrieved from either the battery or the energy-harvesting circuit into a suitable energy level, which can be used to supply the electronics of the node. Using energy harvesting helps to reduce the dependency on the battery power by extending the lifetime of the node itself [78]. The communication unit contains the radio transceiver module used for wireless communication. The processing unit is the core of the node, where all data processing and node activity is carried out. The last unit contains the embedded sensors, which can be either passive or active and are responsible for the sensing and actuating tasks. Basically, the effective lifetime of the node is dependent on the available, residual energy and the required amount of energy to successfully carry out the assigned task. Consequently, the total energy consumption is deducted in relation to the energy supply and energy consumption during data processing and communication. Considering the energy provided by the harvesting module and the module consumption, the effective residual energy at a time instance t is estimated in accordance with the consumed, harvested and residual energy amounts of the previous time instance.

$$E_{Res}(t) = E_{Res}(t-1) - E_{Cons} + E_{Harv} \tag{4}$$

$E_{Res}(t)$, $E_{Res}(t-1)$, E_{Cons} and E_{Harv} are the residual energy of the node at a time instance t, the residual energy at a time instance $(t-1)$, energy consumption and the energy of the harvesting module, respectively (see Appendix A).

The general definition of the energy consumption within a sensor node is presented in Equation (5).

$$E_{Cons} = E_{Transceiver} + E_{System} + E_{Sensing} \tag{5}$$

where $E_{Transceiver}$, E_{System} and $E_{Sensing}$ are the energy consumed during the reception and transmission of data packet, energy consumed within the coding and decoding activities and the energy consumed during sensing activities, respectively.

With respect to the standard energy consumption model, the $E_{Transceiver}$ is presented based on the transmitter and receiver electronic definition as presented in Equations (7) and (9). The total energy consumption, within the radio module during data transmission, becomes:

$$E_{Cons} = E_{R_x} + E_{T_x} + E_{System} + E_{Sensing} \tag{6}$$

The energy of transmission and reception are dependent on the number of transmitted data bits over a distance d, where E_{elec} is the electrical energy of the circuitry needed to transmit or to receive a l bit data packet. d is the distance between the receiver and transmitter.

$$E_{T_x} = \begin{cases} E_{elec} \times l + E_{fs} \times l \times d^2, & d \le d_T \\ E_{elec} \times l + E_{amp} \times l \times d^4, & d > d_T \end{cases} \tag{7}$$

The distance between both transmitter and receiver is dependent on the medium access and therefore, it is defined based on ϵ_f and ϵ_{amp}, which present the energy consumption factor for free space and for the multipath radio models, respectively. The threshold distance d_T is defined as:

$$d_T = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{amp}}} \tag{8}$$

The energy consumption during the reception is defined based on the number of communicated bits l, which is defined in Equation (9). The list of the used parameters with their typical values is illustrated in Appendix A.

$$E_{R_x}(l) = E_{elec} \times l \tag{9}$$

Eventually, the effective energy consumption of a wireless node depends strongly on how often it sends and receives data packets, and processes sensor information.

Task offloading offers a promising solution to reduce the workload on the installed devices, by adopting specific algorithms where the task realization is offloaded to devices with efficient energy sources and computation capabilities. In the context of WBANs and wearable solutions, intensive computing is mitigated from the wireless sensor to the edge and from the cloud to the fog. It presents an efficient solution to manage the intensive communication and computation in a limited energy source environment. Moreover, by adopting an energy-harvesting solution, the energy of the system can be kept available to carry out the assigned tasks in real time and continuously, which remains challenging for different applications, such as in the case of real-time and continuous pulse monitoring [79], motion tracking [80], exoskeleton manipulation [81] and the maintenance and monitoring of implantable devices [82]. To this end, providing continuous and efficient power supply to wearable and implantable devices presents a highly addressed challenge in recent research [83–85]. As part of this, integrating energy-harvesting technologies with task-offloading approaches allows end devices to endure for a long time to support long-term task processing [86–88].

5. Power Supply for Wearables with Task Offloading Capabilities

Task-offloading approaches can be efficiently combined with energy harvesting to address the issue of insufficient battery capacity and limited computation resources in IoMT devices and consequently increase the operating time of wearable devices. This is referred to as joint energy harvesting and task offloading. Using this technology, users can extract energy, convert it into useful energy, store it in the appropriate energy-storage device, and use that energy to perform the corresponding local computing and offloading tasks [15,89–91].

As depicted in Figure 4, the offloading algorithm reacts based on two estimations: The energy harvested/stored and the energy demands. Energy harvesting from ambient sources is considered a promising solution that can be used to provide power supply for IoMT devices and thus replace batteries. The most commonly used harvesters for the supply of wearable devices are piezoelectric harvesters, thermoelectric generators, RF harvesters, and solar cells. Table 4 illustrates the amount of power that can be harnessed from different sources, along with some advantages and limitations associated with each.

Ambient light presents the highest power density among other sources, with the possibility of harvesting indoor and outdoor. However, it has limited application due to its restricted availability.

Table 4. Available power from different energy sources (literature survey).

<table>
<tr><th>Energy Source</th><th>Harvested Power</th><th>Advantages</th><th>Disadvantages</th></tr>
<tr><td colspan="4">Mechanical energy</td></tr>
<tr><td>Human (motion)</td><td>4 μW/cm^2</td><td rowspan="2">High power density</td><td rowspan="2">Depending on the source properties</td></tr>
<tr><td>Industry (vibrations)</td><td>100 μW/cm^2</td></tr>
<tr><td colspan="4">Thermal energy</td></tr>
<tr><td>Human (heat)</td><td>25 μW/cm^2</td><td rowspan="2">Widely available</td><td rowspan="2">Limitation of power density</td></tr>
<tr><td>Industry</td><td>1–10 mW/cm^2</td></tr>
<tr><td colspan="4">Ambient light</td></tr>
<tr><td>Indoor</td><td>10 μW/cm^2</td><td rowspan="2">High power density</td><td rowspan="2">Intermittent</td></tr>
<tr><td>Outdoor</td><td>10 mW/cm^2</td></tr>
<tr><td colspan="4">Radio frequency</td></tr>
<tr><td>GSM</td><td>0.1 μW/cm^2</td><td rowspan="2">Widely available</td><td rowspan="2">Power dependent on distance between RF source-harvester</td></tr>
<tr><td>Wi-Fi</td><td>0.001 mW/cm^2</td></tr>
</table>

5.1. Thermoelectric Generators

Energy can be derived from heat using thermoelectric generators (TEGs) based on the thermoelectric effect. It is also known as the Seebeck effect, according to which electricity is generated by the temperature gradient between two conductors. A TEG can be attached to the body to convert the temperature difference between a body skin and the surrounding environment into voltage. This concept was launched in 1999, where the first wristwatch supplied by body heat was invented [92]. TEGs can be used as an efficient power supply for wearable devices when the human body and the surrounding environment have a temperature difference of 5 to 10 degrees.

The electric potential of a TEG is expressed by Equation (10)

$$V_{TEG} = S \cdot \Delta T \quad (10)$$

where S is the Seebeck coefficient of the material used and (ΔT) is the temperature difference across the TEG.

A thermally powered wearable device that incorporates an accelerometer to sense falls was developed in [93]. In this application, the device generated 520 µW of output power at 15 °C, which charged a capacitor and a power management unit, included to link the thermal source and a sensor node.

An in-depth analysis of thermoelectric generation technology was recently presented in [94], illustrating the working principles of TEGs and their applications. Nevertheless, the development of thermoelectric materials with acceptable power factors remains a major challenge, for which various techniques have been investigated to achieve better efficiencies.

5.2. Kinetic Energy Harveters

In contrast to solar or thermal energy, a kinetic energy source is not dependent on location or time. Kinetic harvesters are based on the extraction of vibration or motion and the conversion of the mechanical energy into electrical power through one or a combination of different transduction mechanisms. The most common ones are piezoelectric, electromagnetic, electrostatic, and triboelectric. These harvesters are classified related to their transduction mechanisms. Unlike other means of transduction, piezoelectric harvesters directly convert human motion changes into electrical signals without any requirements for further external input. Piezoelectric (PE) harvesters operate through the piezoelectric effect. When a force is applied to a PE element, a mechanical strain is developed, causing the material to exhibit changes in its polarization, causing the accumulation of electrical charges across the piezoelectric material. The changes in charge distribution produce an electric field depending on the applied force, frequency of oscillation, and geometry of the harvester.

Electromagnetic kinetic energy harvesters operate based on Faraday's law induction which states that once a conductor moves through an electric field, a current is induced. A system of springs, magnets and coils are used in electromagnet energy-harvesting systems. Coil number and magnetic mass are the main determinants of the output power of these energy harvesters. Therefore, reducing their size, weight and complexity is challenging. As example, the authors of [95] demonstrated the effectiveness of a frequency-converted electromagnetic harvester which extracts energy mainly from human limb motion. A power density of 0.33 mW/cm^3 was achieved in this work using low-frequency human vibration to power wearable devices at extremely low frequencies.

5.3. Flexible Piezoelectric Generators

The body is an excellent source of significant amounts of mechanical energy which can be produced from several biological processes, including walking, heartbeat, breathing and muscle movements. Thanks to their high flexibility, piezoelectric nanogenerators (PENGs) can convert this mechanical stress into electrical charges through nanostructured piezoelectric materials when stretched, pressed or flexed. In addition, this technology can potentially be integrated with other energy-harvesting mechanisms, resulting in hybrid energy-harvesting solutions. The simple architecture of PENGs makes them attractive and considered to be the most promising energy harvesters for wearable devices and microsystems. The materials used in piezoelectricity are diverse, including crystals, ceramics, and polymers. The converter needs to be attached to a part of the body subjected to strong compressive stress to maximize the piezoelectric effect. PENGs can provide enough power to supply devices with power consumption ranging from microwatts to milliwatts, which best fits the wearable sensor range as seen in Table 5 where the energy consumption of typical wearable sensors is presented.

Table 5. Energy consumption of typical medical sensors.

Wearable Sensors	Voltage Range	Power Consumption	Description
Optical heart rate sensors - BH1790GLC optical heart rate sensor [96]	1.7–3.6 V	720 µW	Measures the pulse waves that occur when the heart pumps blood.
Blood pressure sensors - Capacitive tactile sensor [97]	1.8–3.3 V	1.2–4.6 mW	Measures the pressure exerted by the circulating blood on the walls of blood vessels.
Glucometers - Implantable RFID glucose monitoring sensor [98]	1.0 V–1.2 V	50 µW	Measures the average blood glucose concentration.
Pulse oximeter sensors -MAX30102 pulse oximetry [99]	1.8 V–3.3 V	<1 mW	It attaches to a body part, most commonly to a finger to measure the oxygen saturation level of the circulating arterial blood.

Flexible Piezoelectric generators can be modeled as sinusoidal current sources I_P in parallel with parasitic capacitances C_P and internal resistances R_P when excited by sinusoidal vibrations at their resonant frequencies. Since the piezoelectric transducer can deliver an alternating irregular AC current rather than direct current (DC), an electronic interface is essential to enable voltage compatibility between the piezoelectric element and the load. The electronic interface greatly influences the energy-harvesting effectiveness [100], which has driven a variety of research efforts to develop PENG-compatible energy management interfaces [101]. Implementing these circuits is mostly intended to allow the user to use irregular AC power harnessed by piezoelectric transducers (PTs) to supply loads such as wearable sensors. The rectification stage of PEH systems is usually coupled with a DC-DC converter [100] to scale the rectified voltage to match the application's requirements.

One limitation of the classic AC-DC energy-harvesting circuits when implemented with PEts is that negative output power is produced because the output current and voltage could not keep the same phase, leading to a loss of an amount of the harvested energy. P-SSHI and S-SSHI have been proposed to overcome this limitation. The main difference between the circuits is how we connect the switch S and the inductor L, either in series, so we are talking about SSHI or in parallel to deal with P-SSHI. When the vibration occurs, the switch S remains open, allowing the current to flow through the circuit to the storage element Cr. If the piezoelectric element's voltage drops below a certain threshold, the switch S will automatically close, inverting the voltage across the PE element and therefore stopping current flow. This means that the switch is kept closed until a full inversion of the PEt's voltage has been achieved. Nevertheless, this voltage inversion causes an electrical damping that opposes the mechanical vibrations on the piezoelectric material. This effect is known as Synchronized Switch Damping (SSD). It can significantly affect the overall conversion efficiency, and it is consequently the main limitation of both P-SSHI and S-SSHI circuits. Figures 6 and 7 display the P-SSHI and S-SSHI energy-harvesting interfaces, respectively.

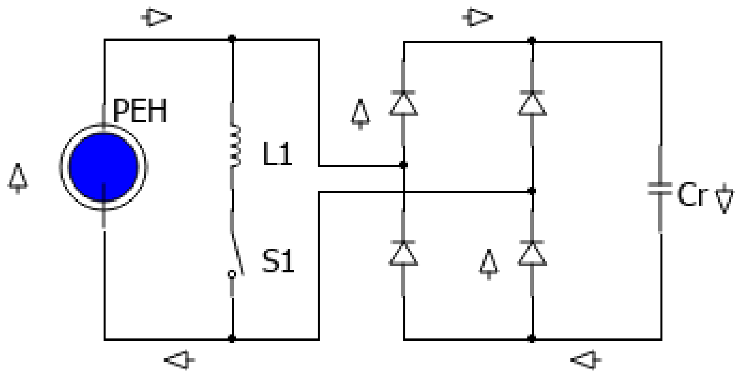

Figure 6. Schematic of P-SSHI energy extraction interface.

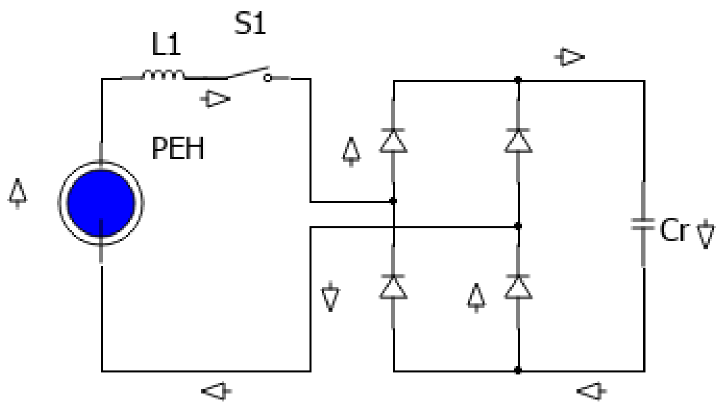

Figure 7. Schematic of S-SSHI energy extraction interface.

SECE circuit, displayed in Figure 8, mainly prevents the SSD effect, which is the main limitation of P-SSHI and S-SSHI circuits. This effect is caused by the direct connection between the output load and the piezoelectric transducer during the hole vibration phase. When the PEH generates the voltage, the switch S will be closed, and the energy will be stored in the inductor L as seen in the figure.

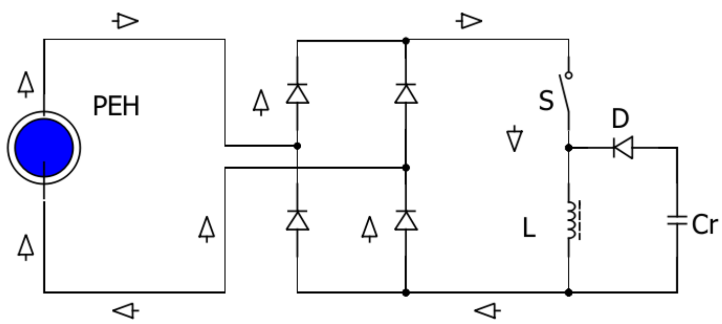

Figure 8. Schematic of SECE energy extraction interface when the switch S is closed.

When the vibration stops, the voltage across the piezoelectric element falls to zero, and the switch S will open immediately. Consequently, the energy accumulated in the inductor will be directly transferred to the storage capacitor and the load. One limitation for this interface is the complexity when compared to the simple architecture and switching strategy that characterize SSHI circuits.

The control of the integrated switches was a common limitation for the reviewed interfaces, so several researchers were focusing on developing self-powered resonant energy-harvesting circuits. In [102], authors demonstrated an optimized self-powered P-

SSHI circuit that can automatically switch once the voltage exceeds its maximum threshold. In addition, this technology can potentially be integrated with other energy-harvesting mechanisms, resulting in hybrid harvesting solutions [103].

5.4. Energy-Storage Techniques

Using energy harvesting to achieve battery-free operation has gained high interest. However, any interruption in the energy-harvesting source will affect the wearable device's operation. Therefore, an energy-storage mechanism is still required to maintain a smooth power supply for charge loads and serve as a backup whenever the energy source is unavailable.

The harnessed energy can be stored before being supplied to the MCU, or the power can be delivered directly. The decision of whether implementing a storage element in a wearable device considers different factors:

- Placement of the device: implant or outside.
- Energy source: type
- Requirements of the application: either it needs a sustainable supply for the wearable device or a non-critical usage.

Batteries and super capacitors are the two main solutions for energy storage. Energy storage for wearable devices must comply with several requirements. First, the storage element needs to be rechargeable to avoid frequent battery replacements, which can be inconvenient in several cases. In pacemakers, as an example, surgery needs to be performed every eight years to replace their lithium batteries [104]. As a second requirement, the storage device needs to be capable of supporting long-term application with minimal impact on battery parameters.

The following Table 6 compares two storage mechanisms, batteries and capacitors.

Table 6. Comparison between different storage techniques for energy harvesters in IoMT devices

Comparison	Conventional Batteries	Supercapacitors
Storage mechanism	Chemical	Physical
Energy storage	High	Limited
Recharging cycles	100 s	Millions
Charging time	Hours	Sec-minutes
Impedance	Low-high	Low
Physical size	Large	Medium
Capacity	0.3–2500 mAH	10–100 µAH

They differ mostly in the number of charging cycles since capacitors can reach millions of cycles. In addition, capacitors require only a few seconds for charging, so the charging time is very fast compared to batteries. In contrast, supercapacitors cannot be used in AC and high frequency circuits and have lower capacity than batteries, but this can satisfy the requirements of some low-power applications. One more limitation for using batteries as a storage element is that the battery is susceptible to leakage, leading to chemical poisoning, especially when used in implants. Batteries can leak chemicals when overcharged or heated (above 60 °C). This can lead to chemical burns risking human beings. Due to their advantages over batteries, super capacitors are a promising alternative to store energy. In a super capacitor, thin dielectric layers and electrodes hold power at the electrode–electrolyte interface to be accessed when needed. Thanks to their high pulse power capacity, they can also handle small power surges. Super capacitors' excellent cycle lifetime also makes them ideally suited to act as energy-storage components in energy-harvesting-based sustainable power systems.

5.5. Recent Energy-Harvesting Solutions for Wearables

The human body can be a versatile source of energy harvesting [105,106]. Energy can be harvested from everyday activities, such as breathing, arm motion, walking, running, or pedaling, without performing a specific workout. The body can produce mechanical energy through various body zones movements, such as the elbow, the knee, the ankle or the heels. The performance of three vibrating generators was studied in [107] at nine different body locations for a person walking on a treadmill. The results indicate that the energy generated at lower-body locations (hip, knee, and ankle) is four times greater than the energy generated at upper-body locations. Additionally, body heat offers promising possibilities for supplying wearable systems. Based on the Seeback effect, a flexible TEG generated 4.95 mW of body heat and was used for a wearable multi-sensing bracelet [108]. A energy-autonomous, multi-sensing bracelet can operate under varying conditions, including human motion. The amount of energy in such systems is highly dependent on the temperature difference between the human body and the ambient environment [109]. Several studies have shown that physiological activities, such as blood pressure, heart motion and breathing, can regularly provide wearable devices with energy supply. In [110], cardiac contractions are used to supply low-powered pacemakers. When powered by a constant heartbeat of 90 bpm, the harvester can deliver 11.1 j of electrical energy. Because of the small size and weight requirement, energy extraction from the human body is much more complicated than energy harvesting from machines [111]. The available power is often weak and difficult to use, such as human kinetic energy, which typically has a low frequency and a low amplitude.

Recently, thermoelectric nanogenerators (TENGs) were demonstrated as a conventional technique for rehabilitation in [112]. As an exercise gaming device, a wearable TENG-based rehabilitation device (Rehab-TENG) was developed. The device was used to control a game on a laptop by flexing and extending the arm. It is an effective way of testing the motor function of an impaired arm. Rehab-TENG is also used as an energy harvester in an exercise system where the patient moves an impaired arm to store energy in a capacitor. It is possible to assess the level of deficiency by measuring the charging rate of the storage element, which consequently enhances patients' motivation for exercising more repetitive movements of the impaired body zone. This, in turn, speeds up recovery. Furthermore, the authors suggested using the Rehab-TENG device as an autonomous home exercise and monitoring system, which is particularly relevant during pandemics, therefore reducing the necessity for hospital visits for rehabilitation.

An emerging trend in energy-harvesting technologies for IoMT is developing biocompatible wearable harvesters, such as textiles, footwear, or watches, which are energy-autonomous, lightweight, flexible, and have more computational resources for better performance. Consequently, various energy-saving approaches were proposed to mitigate the problem of excessive energy demands during the operation of devices. Task offloading is a promising and effective technique that extends the operating time of wearables by migrating the energy intensive task to edge device. Task-offloading algorithms attempts to solve an optimization problem by looking for a suitable remote processor to perform the offloading, taking into consideration the overheads caused by the communication link (energy and latency). Real-time implementation of task offloading for wearables is still in its infancy.

6. Value-Based Healthcare System and Personalized Healthcare

The legacy health care system is staff-centric. Driven by the need to transform the healthcare system to be patient- and personnel-centric, numerous governments have proposed a transformation strategy. For instance, in Saudi Arabia, the government has identified eight challenges that the current health care system should cope with. Those challenges are: (1) the continued growth and aging of the population, (2) the prevalence of avoidable injuries and non-communicable diseases beyond the international standard, (3) the inadequacy and inconsistency of primary care, (4) wide-scale disparity in the quality of care, (5) a significant deficiency in value and quality, (6) the system is resource-, staff-, and institution-centric, (7) insufficient use of digital integrated systems, and (8) the growing need to decrease government spending in health care systems [113].

The value-based healthcare system is a new framework adopted by many governments to improve healthcare services and user experience through the improvement of patient healthcare outcomes at the lowest possible cost, i.e., the value is determined as the ratio of outcomes to cost [114]. Preventive medicine and early intervention lowers the cost associated with the hospitalization of patients. Healthcare 4.0, a new paradigm shift in the health industry, has transformed healthcare from an institution-centered to a patient-centered system [115].

Wearables are cornerstone technologies in Healthcare 4.0. The design of patient-centered care mandates the inclusion of the user requirements to identify functional and non-functional requirements [35]. Surveys, focus groups, and interviews are common ways to capture user requirements. In [116], the authors devised a cost-efficient system for the monitoring of the sedentary level of senior citizens. The system requirements and guidelines have been gathered from a literature review. The system is then evaluated using a mixed approach: focus group, interview, and observations. The system is refined through the feedback provided by the end-user. The authors reported that: (1) the majority of the respondents are interested in receiving a feedback on the level of their physical activity at the end of the day, (2) nearly 58% of participants showed interest in a system that integrates games with physical activity, and (3) virtually 83% of the participants showed interest in profiling their daily activities and receiving alerts when their physical activities are low.

The user requirements for the wearables targeting Chinese seniors are the focus of the work described in [117]. Those requirements have been classified under the following three categories: healthcare requirements, privacy and security requirements, and commodity requirements.

7. Conclusions

Wearable devices are the heart of IoMT. Energy-harvesting techniques can achieve energy-autonomous wearable devices. However, handling tasks that require intensive computing resources limits their performance. To overcome these limitations, energy-aware task-offloading approaches were proposed to reduce the device energy consumption and improve computation resources. This paper surveys recent works on joint task offloading and energy-harvesting techniques in the IoMT. In addition, possibilities of power supply for medical sensors and energy-storage strategies are investigated.

Joint task offloading and energy harvesting is still an active area of research. The offloading is meaningful at two possible levels: from wearables (IoT end device) to edge devices (IoT high-end or middle-end device), or from edge devices to fog nodes. An off-policy-based reinforcement learning algorithm has been often proposed in the literature. Nevertheless, its hardware implementation has received scant attention.

Future work will focus on the efficient hardware implementation of joint energy harvesting and reinforcement learning-based task offloading for wearable devices. Nevertheless, privacy and security might affect the offloading strategy when applied to wearables; this topic was not considered in this study.

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Abbreviations

EH	Energy Harvesting
SSHI	Synchronized Switch Harvesting on Inductor
P-SSHI	Parallel Synchronized Switch Harvesting on Inductor
S-SSHI	Serial Synchronized Switch Harvesting on Inductor
SECE	Synchronized Electrical Charge Extraction
SEH	Standard Energy Harvesting (Bridge rectifier)
SSD	Synchronized Switch Damping
EWMA	Exponentially Weighted Moving Average
HBC	Human Body Communication
IoT	Internet of Things
IoMT	Internet of Medical Things
MCU	Micro-Controller Unit
MEC	Mobile Edge Computing
QoS	Quality of Service
WBANs	Wireless Body Area Networks
WSNs	Wireless Sensor Networks
PENGs	Piezoelectric nanogenerators
PEH	Piezoelectric energy harvesting
FPEGs	Flexible Piezoelectric Generators
PEt	Piezoelectric transducer
TEG	Thermoelectric Generator

Appendix A

Table A1. List of parameters with their typical values.

Parameter	Explanation	Typical Value/Range	Unit
$E_{Res}(t)$	Residual energy at a time instance t	NA	J
$E_{Res}(t-1)$	Residual energy at a time instance $(t-1)$	NA	J
E_{Cons}	Energy consumption	NA	J
E_{Harv}	Energy of the harvesting module	NA	J
$E_{Transceiver}$	Consumed energy of transmission	NA	J
E_{System}	Consumed energy of coding and decoding	NA	J
$E_{Sensing}$	Consumed energy of the sensing	NA	J
E_{R_x}	Consumed energy of the reception	NA	J
E_{T_x}	Consumed energy of the transmission	NA	J
E_{elec}	Electrical energy of the circuitry	Based on initial assumption (e.g., 50 nJ)	J
d	Distance between transmitter and receiver	Related to the realized scenario	m
d_T	Threshold distance between transmitter and receiver	1 m	m
l	Size of the data packet	Depends on the ADC of the processor	bits
ϵ_f	Energy consumption factor for free space	Depends on the	pJ/bit/m^2
ϵ_{amp}	Energy consumption factor for multipath radio models	propagation loss	pJ/bit/m^4
M	Number of cores	8	-
n	Number of tasks	maximum value is 6	-
α	the learning rate	10^{-4}	-
γ	the discount rate	0.85	-

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