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Task Scheduling for Energy Harvesting-based IoT: A Survey and Critical Analysis

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***Abstract*—The Internet of Things (IoT) has important applications in our daily lives including health and fitness tracking, environmental monitoring and transportation. However, sensor nodes in IoT suffer from the limited lifetime of batteries resulting from their finite energy availability. A promising solution is to harvest energy from environmental sources, such as solar, kinetic, thermal and Radio Frequency (RF) waves, for perpetual and continuous operation of IoT sensor nodes. In addition to energy generation, recently energy harvesters have been used for context detection, eliminating the need for conventional activity sensors (e.g., accelerometers), saving space, cost, and energy consumption. Using energy harvesters for simultaneous sensing and energy harvesting enables *energy positive sensing* – an important and emerging class of sensors, which harvest more energy than required for context detection and the additional energy can be used to power other components of the system. Although simultaneous sensing and energy harvesting is an important step forward towards autonomous self-powered sensor nodes, the energy and information availability can be still intermittent, unpredictable and temporally misaligned with various computational tasks on the sensor node. This paper provides a comprehensive survey on task scheduling algorithms for the emerging class of energy harvesting-based sensors (i.e., energy positive sensors) to achieve the sustainable operation of IoT. We discuss inherent differences between conventional sensing and energy positive sensing and provide an extensive critical analysis for devising revised task scheduling algorithms incorporating this new class of sensors. Finally, we outline future research directions towards the implementation of autonomous and self-powered IoT.**

***Index Terms*—IoT, Wearables, Energy Harvesting, Ubiquitous Computing, Sensing, Task Scheduling, Energy prediction**

I. Introduction

WITH the advancements in Micro-Electro-Mechanical Systems (MEMS), low power miniaturized sensors in IoT are becoming popular for monitoring the physical attributes in various applications including surveillance, smart cities, healthcare, exploration of mines, battle field monitoring and even deep sea exploration [1]–[11]. These miniaturized and resource constrained sensor nodes are deployed in the physical world that work collectively to gather the required information and this phenomenon is often renamed and redefined as *ubiquitous sensing*, *smart dust* and *IoT* [12]. Due to their popularity, smart IoT devices have an increasing share in the global market, which is expected to reach USD 1.6 trillion by the year 2025 [13]. However, conventional sensor nodes employ rechargeable batteries, which have limited energy storage capacity [14] and thus hinder their perpetual and autonomous operation. Although battery technology has evolved over time, batteries still need to be recharged or replaced regularly to ensure the sustainable operation of IoT [15], [16]. This impedes the pervasive use of sensors and their wide spread deployment in IoT applications, in particular, the ones that require a large number of sensors, such as in smart cities and deep sea exploration. In order to solve this problem, energy harvesters such as kinetic, solar, thermal, and RF [17]–[19] have been used to convert the environmental energy into electrical energy, to extend the battery lifetime of sensor nodes [20], [21]. This mitigates the issue of limited battery lifetime, and thus allows the autonomous operation of sensor nodes in Energy Harvesting-based IoT (EH-IoT), minimizing the need for human intervention.

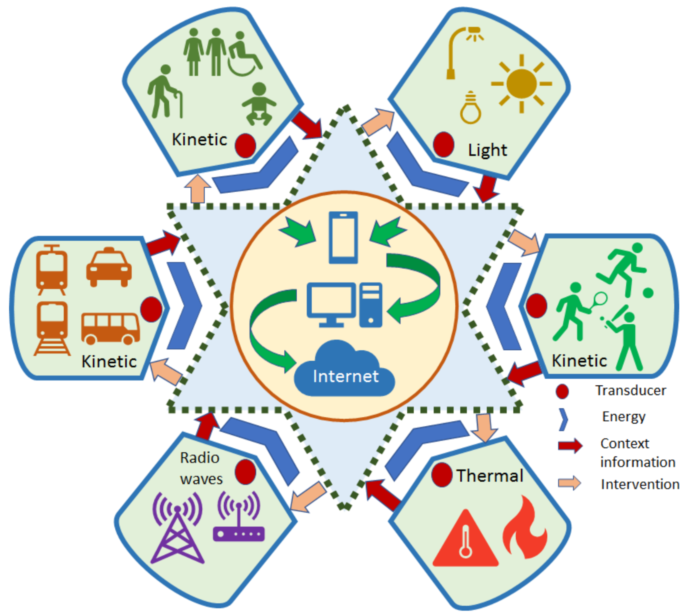

Fig. 1. Energy harvesters can be used as context sensors as well as source of energy in IoT.

Recently, in addition to energy scavenging, energy harvesting transducers have been used as a source of context information in various applications, including transport mode detection, gesture recognition and human activity recogni-

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TABLE I
COMPARISON OF THIS WORK WITH PREVIOUS SURVEY PAPERS RELATED TO EH-IOT AND TASK SCHEDULING RESEARCH

Year	Reference	Energy harvesting	Task scheduling
2006	[42]	×	✓
2008	[43]	×	✓
2010	[44]	✓	×
2013	[45]	×	✓
2014	[46]	✓	×
2016	[47]	×	✓
2016	[48]	✓	×
2018	[49]	✓	×
2020	[50]	✓	×
2020	Proposed	✓	✓

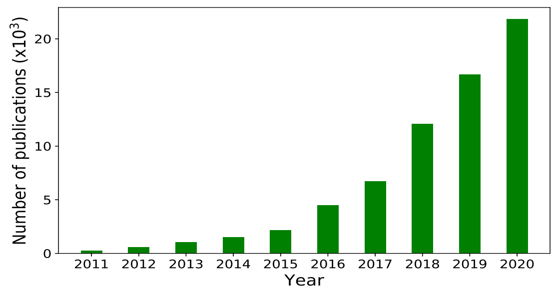

Fig. 2. Research trend in the previous years depicts the growing potential of publications containing the following keywords: *Energy harvesting IoT, Task scheduling in IoT, and Batteryless IoT.*

tion [22]–[24]. This allows saving of sensor-related energy consumption [24] that would otherwise be used for powering conventional activity sensors, such as accelerometers. Fig. 1 demonstrates the simultaneous sensing and energy harvesting paradigm where energy harvesters are employed as energy efficient activity sensors to detect the underlying activity, in addition to being a source of energy to power the sensor nodes. In this paradigm, the harvested energy can be used to power various components of the system, e.g., the signal acquisition, activity detection and data transmission leading towards energy positive sensing [25], [26], and potentially autonomous operation of sensor nodes in EH-IoT.

Despite the emerging importance of EH-IoT, the amount of generated energy from the ambient environment is still insufficient to enable the Energy Neutral Operation (ENO) [27] of miniaturized sensor nodes [28], especially for wearable sensing devices that have a small form factor. Various research efforts have been made to achieve ENO of miniaturized sensor nodes, such as maximizing the harvested energy by implementing optimal energy harvesting mechanisms [28], [29], minimizing the energy consumption [30] by using novel low power sensing mechanisms such as energy harvesting-based sensing [24], and considering multi-source energy harvesters [31] that harvest energy from multiple sources. However, the amount of generated energy from the ambient environment can still be inadequate to fully power the IoT sensor nodes. Therefore, energy management algorithms are needed to manage the precious and limited harvested energy, ensuring ENO of sensor nodes [32]. There are different types of energy management algorithms, including transmission power control [33]–[35], Medium Access Control (MAC) [36]–[38] and task scheduling [39]–[41], to name a few.

Task scheduling algorithms are employed to schedule the broader set of tasks (such as sampling, processing, and transmission) on the sensor node, according to the available energy budget, to prolong its operational lifetime. It is an effective method to minimize the energy consumption on the sensor node, due to its direct interaction with the Energy Storage Unit (ESU) (i.e., battery/capacitor) and energy consumption (in executing the tasks) on the processor. Task scheduling algorithms can be more effective in minimizing the energy consumption, compared to other communication-focused energy management schemes (i.e., transmission power control). This is due to their interaction with a broader set of tasks including digitizing, sampling, and processing as well as communication. The objective of task scheduling algorithms is to run sensor nodes using the unreliable harvested energy [51], [52] to ensure ENO and achieve maximum sensing performance in IoT applications. Therefore, in this survey, we comprehensively analyze task scheduling algorithms for energy harvesting-based sensing to enable the ENO of sensor nodes in EH-IoT.

A. Motivation

In recent years, there has been a growing trend in energy harvesting mechanisms to power IoT sensors and related task scheduling-based energy management algorithms, as depicted in Fig. 2[1]. The figure portrays the number of research publications per year that contain any keyword from *Energy harvesting IoT, Task scheduling in IoT, and Batteryless IoT*. Task scheduling algorithms are incorporated in EH-IoT to ensure ENO of sensor nodes using the limited, unreliable and time-varying harvested energy. In addition to energy generation, energy harvesters have been recently used for activity recognition [22], [24], [53], as depicted in Fig. 1, representing a rich information source which can replace conventional activity sensors that require continuous power to operate.

Using energy harvesters as a simultaneous source of energy and context information enables the energy positive sensing concept [25], [26], which allows the transducer to harvest sufficient energy to power the sensor node. The ability to extract information from energy harvesting signals, and in most cases to gain energy in the process, can significantly impact the task scheduling landscape for EH-IoT as described in Section IV. Therefore, task scheduling algorithms need to consider the information and energy gain (for energy positive sensing), rather than energy loss, of different sensors to achieve their objective. This potential warrants a comprehensive survey of task scheduling algorithms to analyze their support for such decisions.

[1]The numbers are obtained from *Dimensions*.
Source: https://app.dimensions.ai/discover/publication
Accessed on: March 26, 2021

B. State-of-the-art

There are several works in the literature that explore task scheduling in EH-IoT. Table I compares our paper to previous survey papers related to IoT with energy focused research. Some of the previous works [42], [43], [45], [47] present extensive surveys on task scheduling algorithms to minimize energy consumption. However, none of theses surveys considered energy harvesting mechanisms to power batteryless IoT sensor nodes with the associated opportunities and challenges compared to battery-powered IoT. Other survey papers [44], [46], [48], [49] covered energy harvesting mechanisms to power IoT sensor nodes in order to enhance their operational lifetime and to reduce maintenance cost as given in Table I. However, they considered conventional sensors instead of energy harvesting-based sensing. A recent comprehensive survey [50] is the first to cover energy harvesting-based sensing while exploring sensing, computing and communication for EH-IoT. However, none of previous survey papers on energy harvesting research [44], [48], [49], including this most recent one [50], considered task scheduling as a crucial mechanism to manage the execution of tasks under the limited and time-varying harvested energy. Furthermore, to the best of our knowledge, there is no previous work that explores the potential and associated challenges of implementing task scheduling algorithms for the emerging class of energy positive sensors.

C. Contributions

To address the aforementioned gaps in the literature, this work critically surveys task scheduling algorithms to minimize the energy consumption for perpetual operation of sensor nodes in EH-IoT, and analyzes their potential to support energy harvesting-based sensors. Our contributions are as follows:

- We discuss the implementation of energy harvesters as sensors and energy sources simultaneously, which is advantageous in practical environments leading towards self-powered batteryless IoT. We also explore the concept of energy positive sensing, which uses the harvested energy to acquire the energy harvesting signal for sensing and activity detection, in contrast to the conventional energy negative activity sensors which rely mainly on external energy sources.
- We analyze task scheduling based energy management algorithms for implementing the tasks on resource constrained sensor nodes under limited and varying harvested energy due to unreliable environmental energy (i.e., kinetic, solar, thermal, RF waves, etc).
- Based on an extensive study of the literature, we comprehensively describe the key challenges and potential solutions when integrating energy positive sensing with conventional task scheduling algorithms.
- Finally, we present future research directions to enable the sustainable and autonomous operation of batteryless sensor nodes in EH-IoT.

The remainder of this paper is organized as follows: Section II comprehensively describes energy harvesting-based IoT covering the previous works related to energy harvesting to power IoT, mechanisms of energy harvesting, estimating battery State of Charge (SoC) and sensing using energy harvesters. Task scheduling algorithms for EH-IoT are presented in Section III along with energy prediction algorithms, to ensure the perpetual operation of sensor nodes. Section IV critically analyzes the challenges and opportunities for modifying task scheduling algorithms for the new class of energy positive sensors. Future research directions are described in Section V and finally, Section VI concludes the paper.

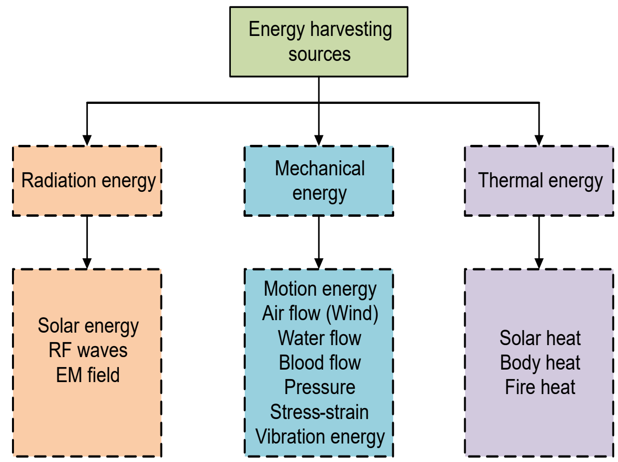

Fig. 3. Energy harvesting sources can be classified into various categories depending upon the type of energy.

II. Energy Harvesting-based IoT

This section presents a background of EH-IoT, covering the literature related to energy harvesting to power IoT sensor nodes, energy harvesting mechanisms, battery SoC estimation, as well as the emerging concept of sensing using energy harvesters, which opens the door for revised task scheduling algorithms incorporating this new concept.

A. Energy harvesting to power IoT

Recent advancements in technology have led researchers and companies towards the design and development of low-power energy harvesting circuits [55] to harvest energy from the ambient environment for powering the miniaturized sensor nodes. There are various energy harvesting sources, including radiation energy, mechanical energy and thermal energy as depicted in Fig. 3. Radiation energy is available in various forms, including sunlight, RF waves and Electromagnetic (EM) field. In addition, there is abundant mechanical energy in the environment in the form of motion, water flow, blood flow and stress that can be converted into electrical energy. Thermal energy includes solar heat, body heat and fire heat that can be transformed into electrical energy using a Thermoelectric Power Generator (TEG). Due to the difference in the temperature levels between the upper and lower layers of TEG, a potential difference is developed which forces the current to flow in the circuit. Table II summarizes the characteristics of various energy harvesting sources [54]. RF Energy Harvesting (RFEH) and Thermal Energy Harvesting (TEH)

TABLE II
CHARACTERISTICS OF AMBIENT ENERGY SOURCES [54]

	Solar energy	Thermal energy	RF energy	Piezoelectric energy	
				Vibration	Push button
Power density	100 mW/cm^2	60 μW/cm^2	0.0002 – 1 μW/cm^2	200 μW/cm^3	50 μJ/N
Output	0.5 – 1 V	–	3 – 4 V	10 – 25 V	100 – 10000 V
Available time	Day time	Continuous	Continuous	Activity dependent	Activity dependent
Weight	5 – 10 g	10 – 20 g	2 – 3 g	2 – 10 g	1 – 2 g
Pros	• Large amount of energy • Easy to install	• Always available • Available as wearable	• Light weight and small-sized antenna • Widely available	• Well developed technology • Light weight	• Well developed technology • Light weight
Cons	• Need large area • Not continuous	• Need large area • Low power	• Distance dependent • Depends on power source	• Need large area • Highly variable output	• Highly variable output • Low conversion efficiency

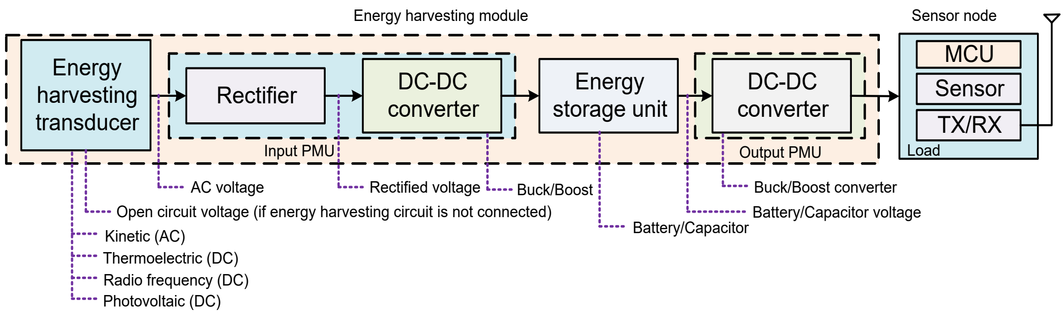

Fig. 4. General system architecture for energy harvesting to power the sensor nodes in IoT.

provide the lowest power levels; however, they can operate almost everywhere due to the presence of ambient RF waves and thermal energy in the environment. On the other hand, Solar Energy Harvesting (SEH) and Kinetic Energy Harvesting (KEH) transducers harvest greater amounts of energy [54], yet they work only under certain environmental conditions, for example, in daylight and under external stimulus, respectively. We describe the state-of-the-art related to energy scavenging from various sources including solar, kinetic, thermal and RF waves, to power IoT sensor nodes in the following part.

1) Solar: Jokic et al. [56] design a wearable smart bracelet that employs a tiny and flexible thin-film photovoltaic panel for harvesting solar energy from the ambient environment. They conduct detailed experiments and find that the flexible photovoltaic panel can harvest $16\,\mathrm{mW}$ of power in outdoor and $0.21\,\mathrm{mW}$ of power in indoor environments. This amount of harvested power is sufficient to acquire one blood oxygenation measurement per minute and to transmit the output via Bluetooth. The authors in [57] employ flexible solar panels and exploit Maximum Power Point (MPP) tracking for harvesting maximum energy to measure the heartbeat using photoplethysmography sensor and monitor the human activity using an accelerometer. Tha authors in [58] propose a regulator circuit to harvest solar energy to power the nodes in a Wireless Sensor Network (WSN). They find that depending on the intensity of outdoor light, the harvested solar power ranges from $220\,\mathrm{mW}$ to $750\,\mathrm{mW}$. Bito et al. [59] design a novel 3-D printed solar and electromagnetic energy harvesting system to power IoT sensor nodes. Their mechanism results in reduced capacitor charging time by 40%, which helps to ensure the perpetual operation of the IoT sensor node.

2) Kinetic: Ambient motion is one of the main sources of energy [60] for powering the sensor nodes in human-centric applications. The authors in [61] study the excitation generated by human movements/vibrations and propose an optimal kinetic harvester geometry for wearable medical sensors. They also propose an efficient KEH circuit to maximize the harvested power. Magno et al. [62] propose an efficient energy harvesting circuit to maximize the energy conversion efficiency from KEH in human-centric applications. They perform extensive experiments and find that their proposed system can harvest on average $624\,\mu\mathrm{W}$ of power from various human movements. Kuang et al. [63] design a kinetic energy harvesting system to generate energy from human knee-joints. They employ MPP to maximize the harvested energy and power the on-body WSN.

3) Thermal: Thermal energy plays a vital role in the design and implementation of autonomous wearable devices for human-centric applications [64]. Proto et al. [65] design a system to harvest thermal energy from the human body during various activities such as sitting, walking, jogging, and riding a bike. The authors in [66] suggest to employ a TEG to harvest thermal energy from the human body to enhance the lifetime of the on-body sensors. Leonov [67] attaches a thermopile with an office shirt and uses it to harvest energy from various subjects in a real life environment. After detailed experiments, it is found that the proposed system can harvest power in the range of $0.5\,\mathrm{mW}$ to $5\,\mathrm{mW}$ at the ambient temperature from $-27\,°\mathrm{C}$ to $15\,°\mathrm{C}$. The authors in [68] propose innovative fiber-based energy conversion devices for harvesting human-body energy. As these devices can be attached with the clothes, they offer higher user-comfort and user-friendless, resulting in long term energy harvesting for the perpetual operation of sensor nodes.

4) RF waves: RF energy offers a promising solution to power IoT sensor nodes when other sources of energy (such as solar and kinetic) are unavailable or when it is infeasible to harvest energy from other sources [69]. Liu et al. [70] propose a theoretical model to harvest ambient RF energy to power the IoT sensor nodes in a smart cities application. The authors in [71] design an energy harvesting circuit to harvest RF energy from various frequency bands, including 700 MHz, 850 MHz, and 900 MHz, to power the sensor nodes. Mouapi et al. [72] propose an RF energy harvesting technique from Industrial, Scientific and Medical (ISM) band (i.e., 2.4 GHz), to power a sensor network for its autonomous operation. The authors in [73] suggest an optimal number and placement of RF energy transmitters to ensure sufficient harvested energy to power the sensor nodes in a terrestrial WSN. However, there are various challenges in designing a completely autonomous RF energy harvesting-based miniaturized sensor node. These challenges include overall conversion efficiency, bandwidth, and form factor [69] in harvesting RF energy from the ambient environment. The detailed mechanisms for harvesting the ambient energy are described in the following subsection.

B. Energy harvesting mechanisms

In general, there are two mechanisms for using the harvested energy to power a sensor node: *harvest-and-store* and *harvest-and-use* [74]. In the former case, the harvested energy is first stored in an ESU, whereas in the latter, the harvested energy from the transducer is directly used to power the system load. In EH-IoT, the harvested energy is time-variant and intermittent, and depends on the external environmental conditions. Therefore, it may not be sufficient to fully power a sensor node in the case of *harvest-and-use*, except when the harvested energy is quite high. In general, the harvested voltage is rectified using a full-wave bridge rectifier, if the energy harvesting transducer produces AC voltage (like in KEH), as depicted in Fig. 4. Then, a DC-DC boost converter [75] is employed to step-up the low harvesting voltage to charge the battery/capacitor. The rectifier and the boost converter constitute the input Power Management Unit (PMU) which is also called Energy Management Unit (EMU), that is situated between the energy harvesting transducer and ESU as shown in Fig. 4. The stored harvested energy is then used to run a sensor/system load through the output PMU, which uses a DC-DC buck converter to regulate and step down the output voltage according to the specifications of the sensor's hardware. However, if the harvested energy from the transducer is sufficient to run the sensor node, the node can be directly powered to avoid the losses in the PMU [76]. The advantage of directly powering the sensor node from the energy harvesting transducer lies in avoiding the energy losses in rectification and charging/discharging the ESU. However, this approach offers unreliable operation of the sensor nodes due to time varying and dynamic characteristics of the environmental energy (i.e., solar, thermal, kinetic and RF). In

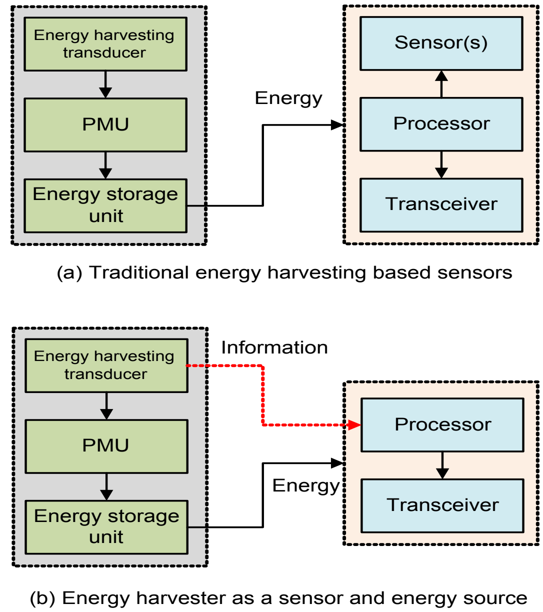

Fig. 5. Energy harvesters can be used as activity sensors, in addition to the energy scavenging.

order to ensure sustained operation of the sensor nodes, the energy harvesting mechanism should be tailored to provide stable, consistent and maximum harvested energy. In order to manage the energy consumption of EH-IoT sensor nodes, it is important to keep track of the harvested energy and dynamic SoC of the battery [77]. Therefore, we explore the previous literature related to the battery SoC estimation in EH-IoT in the following subsection.

C. Estimating the battery SoC in EH-IoT

Estimating the *in-situ* SoC of the battery is crucial for efficiently scheduling the power-intensive tasks on the EH-IoT sensor nodes. Even microscale errors in estimating the battery energy may result in substantial cumulative estimation errors which significantly degrade task scheduling strategies. The authors [78] in present an electronic circuit to continuously monitor the battery energy in sensor nodes. This energy estimation circuit consists of a sense resistor, amplifier, voltage-to-frequency converter, and two counters. Buchli et al. [79] propose a method to estimate the SoC using only the battery voltage. In addition, their method offers higher accuracy with optional current and temperature measurements. In contrast to the previous works which employ dedicated circuits [78] or exploit battery voltage [79], Sommer at al. [80] estimate the SoC using both the net current flow in the battery and the battery voltage. The authors in [81] present a simple model to estimate the battery SoC that entails minimum resources to run on the sensor node. Initially, their method employs various battery parameters and environmental conditions to estimate the SoC. Later on, the previously collected data is used to build a mathematical model based on a linear regression and multilayer perceptron algorithm. Quintero et al. [82] employ a particle filtering algorithm to estimate the battery SoC and

TABLE III
STATE-OF-THE-ART RELATED TO SENSING USING VARIOUS ENERGY HARVESTERS

Energy harvester(s)	References	Target application(s)
Kinetic	[22], [24], [25], [84]–[98]	Airflow speed monitoring, Human step count, Calories burnt, Food intake detection, Hotword detection, Transport mode detection, Ball impact on racket, Human activity recognition, Human gait recognition, Voice demodulation, Knee surgery monitoring, Heart beat monitoring, Authentication key generation
Thermal	[65], [99]–[101]	Water flow detection, Water and appliance metering, Chemical reaction detection, Human activity recognition
Solar	[23], [26], [102]	Hand gesture recognition, Human activity recognition
RF	[103]–[105]	Touch detection, Hand gesture sensing, Hand wash monitoring
Multisource (Kinetic and solar)	[53]	Recognizing places in a built environment

show that it can offer accurate measurement of the battery energy. Most of the battery energy estimation models encompass inherent bias due to the simplifications and assumptions that may results in conspicuous errors in battery SoC estimation. The authors in [83] propose a bias characterization model so that accuracy of the battery energy estimation algorithm can be improved. They employ polynomial regression and Gaussian process regression models to examine the effects of the two methods on bias modeling and the battery SoC estimation, using a typical battery circuit model. Among the plethora of energy harvesting and battery SoC estimation proposals for IoT sensor nodes, some researchers have investigated the use of energy harvesters as a novel context/activity sensor, which we discuss in the next subsection.

D. Sensing using energy harvesters

In addition to energy harvesting, a recent trend is to use the output signals from energy harvesters for extracting context information, as shown in Fig. 5(b), instead of employing dedicated sensors (e.g., accelerometer, magnetometer, etc.), as depicted in Fig. 5(a). Thanks to the varying nature of the harvested energy, it contains the context information about the environment in which the energy harvester is deployed. We summarize the state-of-the-art related to sensing using energy harvesting in Table III. It is evident from the table that various types of energy harvesters, either individually or in combination, have been used as sensors in different applications – leading towards an emerging domain of energy harvesting-based sensing. The harvested energy from a TEH transducer [65], [99]–[101] contains embedded information about the varying temperature conditions in the ambient environment, and thus can be used to detect water flow, chemical reactions and human activities. Similarly, RF harvested energy [103]–[105] varies according to the type of environment and ambient RF energy availability, and thus can be used for

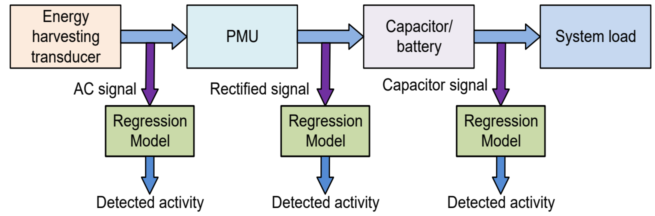

Fig. 6. Energy harvesters have different types of signals for information extraction, such as AC voltage, rectified voltage and capacitor voltage.

touch detection, hand gesture sensing and monitoring the hand wash activity. Furthermore, using the harvested energy from a wrist-worn SEH transducer, human gestures and activities in indoor and outdoor environments can be recognized [23], [26], [102]. Likewise, if the KEH transducer is attached with the wrist wearable device, the output signal provides information about the type of the underlying activity [24]. It is based on the phenomenon that KEH experiences distinct vibration patterns during different human activities, such as walking, running, sitting and standing. These different types of activities leave their distinct signatures in the output signal of KEH. By analyzing the output signal from the energy harvester, it is possible to find the type of activity performed. As KEH provides output due to underlying movements/vibrations, it can be employed as an activity sensor in a variety of applications including transport mode detection, human activity and heartbeat monitoring, and food intake detection [22], [24], [87], [97]. The principal advantage of employing the energy harvester for context detection lies in its sensor-related power saving [24], as compared to the conventional activity sensors (such as accelerometers and magnetometers), which operate on the supplied power from the ESU, as illustrated in Fig. 5.

There are different types of signals in the energy harvesting circuit that can be employed for activity recognition including AC, rectified and capacitor voltages as depicted in Fig. 6. Moving one step further, energy harvesters can be employed as a simultaneous source of energy and context information [25], [106]. This results in full utilization of the energy harvesters to sense the underlying activity and power the sensor nodes. However, the energy harvesting circuit and the operation of load systematically affect the harvesting signals [25], as shown in Fig. 7. This stems from the variance of harvester's impedance [107] with the amount of current drawn by the load. When the load is turned on, it consumes energy and discharges the ESU. This allows the current flow from the transducer to charge the ESU again up to its capacity. When the ESU is full, it blocks the charging current using the rectification circuit in PMU. Thus, various components in the energy harvesting

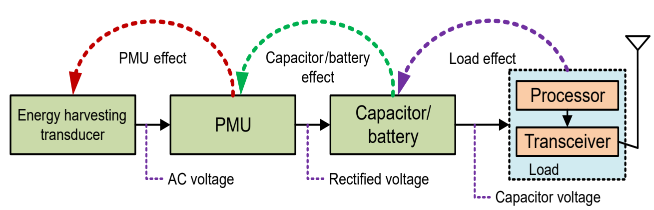

Fig. 7. Impact of load, stored energy and PMU on the harvesting signal of the energy harvesting transducer.

circuit affect the harvesting signals compared to the open circuit configuration which may impact their activity recognition performance [25]. Depending on the type of application, this harvested energy can be higher than the energy required for signal acquisition [25] or for implementing the activity classification algorithm [26] – resulting in energy positive sensing or energy positive activity recognition respectively. This novel class of energy positive sensors can lead towards self-powered and autonomous operation of batteryless EH-IoT sensor nodes.

E. Summary and insights

Energy harvesters serve the dual purpose of energy generation as well as context detection, addressing the requirement of conventional activity sensors, such as accelerometers, magnetometers and gyroscopes. Most of the previous works employ KEH transducers for context detection due to their distinct output signal during different activities. In order to further save the energy consumption, the stored energy in the ESU, sampled at a lower frequency, can be employed for context detection, at the cost of higher latency. However, the harvested energy may still not be sufficient to continuously power a sensor node using miniaturized energy harvesters, e.g., when placed on the wrist in human activity monitoring and fitness tracking applications. This opens the door for energy management algorithms, that schedule the execution of tasks on the node, according to the harvested energy profile, to allow the perpetual operation of the system. In the next section we consider the energy harvesting-based sensing mechanisms, and we comprehensively survey various task scheduling algorithms that manage the time-varying and limited harvested energy on the miniaturized sensor nodes in EH-IoT to ensure their sustained operation.

III. Task Scheduling in EH-IoT

The harvested energy from miniaturized transducers in EH-IoT may not be sufficient to power the sensors nodes continuously without any interruption. Therefore, task scheduling-based energy management algorithms are required in EH-IoT to ensure efficient utilization of the harvested energy. These algorithms ensure optimal utilization of the harvested energy to extend the system lifetime as well as to provide the highest activity detection/monitoring performance. This section describes fundamentals of task scheduling, surveys existing task scheduling algorithms, explores the applicability of task scheduling algorithms for energy harvesting-based sensors and finally discusses energy prediction schemes to ensure energy neutral operation of EH-IoT.

A. Task scheduling fundamentals

Task scheduling is basically used to manage the execution of tasks on the node to maximize the performance in terms of activity monitoring within the limited available energy budget. The most common types of tasks running on a sensor node include sampling of information/signal, digitizing, processing, data storing, transmission and reception, as displayed in Fig. 8.

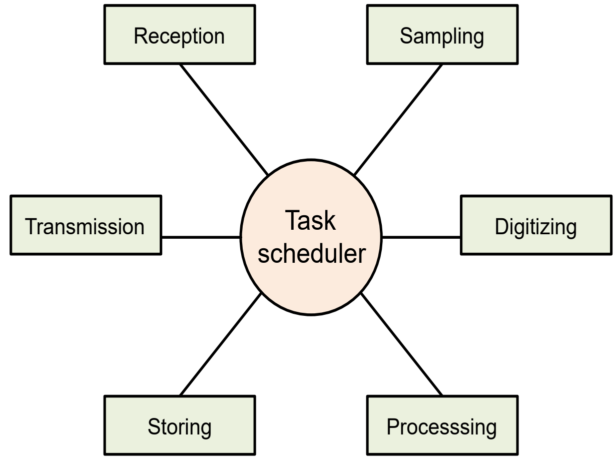

Fig. 8. The task scheduler governs the execution of various tasks on the sensor node in EH-IoT.

According to the type of application, the tasks are scheduled on the node at different frequencies. The task scheduler takes various parameters into account, while scheduling the execution of upcoming tasks, as depicted in Fig. 9. It shows that the task scheduler considers the energy budget, deadline of task, predicted energy and type of task, while scheduling the execution of tasks on the sensor node.

In the literature, most of the task scheduling algorithms consider one or more of the following key principles for scheduling. The tasks are queued according to their priority and order of their deadlines. As long as sufficient energy is available, a high priority task is executed without any delay. If the harvested energy is not sufficient to run a high priority task, the next task in the queue is executed. If energy is not available, the tasks are delayed until their deadlines, to allow sufficient time for the transducer to harvest energy. If a high priority task arrives during the execution of a low priority task, the low priority task is pre-empted (according to the type of application), to execute the high priority task first. Tasks are scheduled according to the energy budget, predicted harvested energy, and deadlines of tasks. Finally, the larger tasks can be broken down into smaller subtasks, which consume small amount of energy and take lower time during their execution. Later, these subtasks can be combined, according to their similarity, to reduce the energy consumption in frequently switching the hardware from idle mode to the active state. We discuss the previous literature related to task scheduling in the following subsection in detail.

B. Task scheduling algorithms

Fig. 10 displays an overview of three major task scheduling algorithms in EH-IoT: (1) Dynamic Voltage and Frequency Scaling (DVFS), (2) Decomposing and combining of tasks, and (3) Duty cycling. We explain these task scheduling algorithms in the following part in detail.

1) ***Dynamic voltage and frequency scaling****:* The power consumption of the sensor nodes depends on the supplied voltage (as well as the current flow) and the operating frequency (i.e., the clock frequency). Therefore, both of these

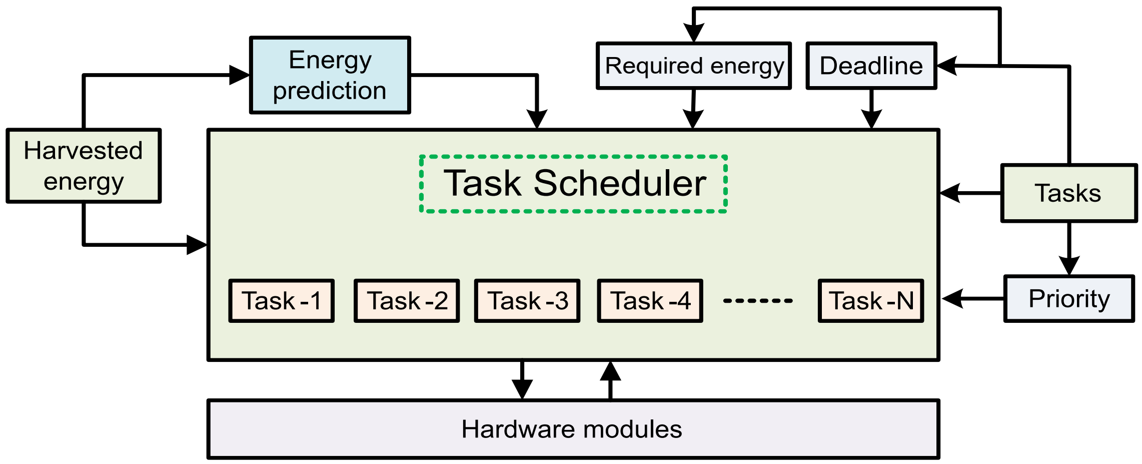

Fig. 9. The task scheduler schedules the tasks based on different parameters including task's energy consumption, deadline and energy budget.

parameters can be adjusted in real-time to optimize the power consumption of the sensor node. The objective of DVFS is to maximize the performance given the limited energy budget or to minimize the energy consumption under a performance bound. The authors in [108] present a task scheduling technique using DVFS for rechargeable sensor nodes. The tasks are grouped according to their deadlines and are executed if the available energy is higher than a certain minimum threshold. Liu et al. [109] propose a scheduling mechanism which slows the processing of tasks according to the available as well as the predicted harvested energy in the future in SEH-based systems. Thus a task is executed at increasing speed as it approaches its deadline. The authors in [110] decouple the energy and timing constraints to simplify the scheduling problem. As a significant amount of harvested energy is wasted in battery leakage, the authors in [111] suggest to switch between the stored energy and direct use of the harvested energy in running the sensor node. This saves the energy that would otherwise be lost due to leakage in a non-ideal ESU. A DVFS based task scheduling algorithm for structural health monitoring is presented in [112]. In this algorithm, both periodic as well as sporadic tasks are scheduled using a linear regression-based algorithm. Liu et al. [113] combine the static and adaptive scheduling techniques with DVFS to attain higher performance with energy and timing constraints. Their algorithm adaptively schedules the tasks when there is a prediction of energy overflow, to achieve the maximum benefit from the harvested energy. Another DVFS based task scheduling framework is proposed in [114]. It employs MPP tracking to harvest maximum energy from the solar cell. This algorithm schedules various tasks on the node according to the predicted energy, available energy budget and the deadlines of tasks, in order to minimize the task drop ratio. Tan et al. [115] model the energy harvesting system as an energy model, a task model and a resource model and present a task scheduling algorithm based on DVFS. Their method combines the free dispersed time slots together, which results in the execution of a higher number of tasks within the limited energy budget.

DVFS algorithms may not be suitable for scheduling tasks on energy harvesting-based batteryless sensors due to the resource-constrained hardware. As the energy harvesting circuits are intentionally kept simple (to avoid energy losses), they may not offer various voltage levels to execute tasks on the sensor node. Therefore, alternate task scheduling algorithms can be employed that work seamlessly without additional overhead in terms of energy and resources, to minimize the energy consumption of resource constrained sensor nodes.

2) ***Decomposing and combining of tasks****:* This algorithm decomposes the energy-intensive tasks into multiple subtasks which demand lower energy during their operation. In general, this decomposing and combining technique consists of the following four phases:

Decomposition: This phase decomposes the energy-intensive tasks into multiple subtasks depending upon their ability to combine with other subtasks to conserve energy. When the harvested energy is not sufficient to run the high-powered tasks continuously, the subtasks can be executed with the limited available energy budget.

Combining: This phase combines multiple subtasks that can be executed on the same processor to minimize the energy consumption. In addition, some tasks can be executed concurrently to reduce the idle time of the processor. For example, the tasks of sensing and fetching stored data from memory can be executed simultaneously depending on the harvested energy as they utilize different resources of the node. The advantage of the concurrent execution is the reduced delay and smaller latency in task execution. However, it also demands higher energy which is available only once in a while in EH-IoT sensor nodes.

Admission control: In this phase, the tasks are filtered according to their priority and energy consumption during their execution. Although tasks are combined to save energy, generally, the harvested energy from miniaturized sensors is insufficient to run all ready-to-execute tasks. Therefore, an admission controller further filters the tasks based on the priority of tasks, available harvested energy and energy consumption of tasks. Task priority is important in all applications and, in particular, for time-critical real-world scenarios. Depending upon the application, the task's deadline is further categorized into two types, i.e. soft deadline and hard deadline. In general, soft

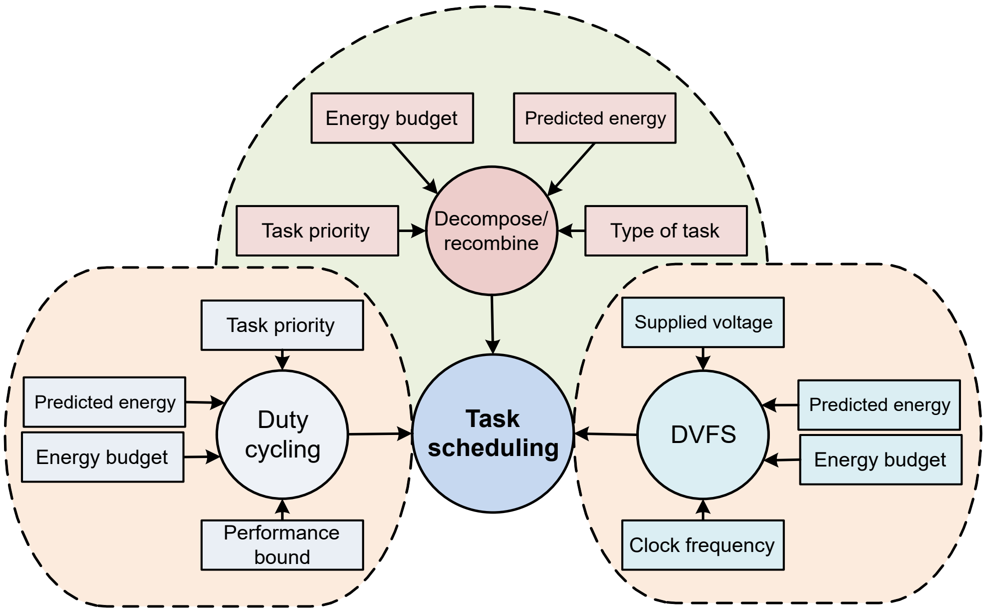

Fig. 10. Different mechanisms for scheduling the tasks on the EH-IoT sensor node.

deadlines are less critical as compared to hard deadlines and their violation does not harm the functioning of the system. On the contrary, hard deadlines are essential to be respected in all circumstances, which create major loss if ignored or violated [116]. Therefore, the admission controller arranges the tasks according to their priorities and deadlines.

Optimization: This phase optimizes the execution of tasks on the basis of additional available energy (available after executing the current task(s)), required number of executions of tasks and the energy consumption of each task. The optimization phase further filters the tasks in order to use the harvested energy efficiently. The additional available energy is important to decide about the execution of future time-critical tasks. In order to avoid deadline violations in the future, a certain minimum amount of energy must be available in the ESU during all time slots, to serve the future tasks that have hard deadlines.

Zhu et al. [117] propose an algorithm of task decomposition and combining to save the energy consumption of sensor nodes. For example, the task of transmitting the sensed data can be decomposed into two separate subtasks of sensing and data transmission. Similarly, the transmission of stored data (in the processor's memory) can be decomposed into the separate subtasks of reading the attribute from memory and data transmission. In order to minimize the energy consumption, the two transmission subtasks can be combined together by grouping the data from these subtasks and transmitting it in one data packet, as shown in Fig. 11 [117]. The authors in [117] evaluate their task scheduling algorithm using SEH as a source of energy. The results show that their technique executes more tasks with fewer missed deadlines as compared to the previous algorithms which do not employ the decomposing/combining algorithm for energy-intensive tasks. In addition to decomposing and combining of tasks, a Markov Decision Process (MDP) model is proposed in [118] to schedule the tasks on the node. It proposes a dynamic optimization model based on MDP to schedule the tasks taking into account their deadlines, energy consumption, and available harvested energy. The decomposed subtasks can be combined together for concurrent execution. It also proposes a less complex greedy scheduling policy which can be implemented on the resource constrained sensor nodes, and which and consumes less energy than the original model. The simulation results indicate that the proposed algorithm [118] executes higher number of tasks within the same energy budget compared to the previous task scheduling algorithms.

As the harvested energy in EH-IoT sensors nodes is limited, they can essentially perform only one atomic task at a time. In the particular case of batteryless sensors, the available tiny energy burst (in the ESU) may not be employed to execute multiple tasks simultaneously [119]. Therefore, combining the tasks to reduce energy consumption may not be appropriate solution for energy harvesting-based sensors. As a result, there is a potential of alternate task scheduling algorithms such as duty cycling to minimize the energy consumption, as elaborated in the following part.

*3) **Duty cycling**:* One of the most familiar and common methods for minimizing the energy consumption in EH-IoT is to use duty cycling or sleep/awake mechanism. When a node does not perform any useful operation, it is switched to sleep mode, which reduces its energy consumption [120]. In traditional IoT, most of the algorithms devise a duty cycling mechanism based on the number of tasks, their energy consumption and remaining energy of the node. However, these methods are not suitable for EH-IoT, due to the variable nature of incoming harvested energy. In EH-IoT, the harvested energy varies significantly due to the change in environmental conditions which effect the ambient energy availability [121]. Therefore, duty cycle of a node must vary depending on the incoming harvested energy as well to efficiently utilize the future harvested energy in executing upcoming tasks on the node. The sleep duration of a node can be adjusted according to the amount of energy to be harvested in the future to proactively plan the consumption of incoming energy for task execution. Therefore, we divide the duty cycling mechanisms into the aforementioned two categories i.e., depending on (1) the current energy budget and (2) the predicted harvested energy, and extensively explore the relevant literature in the following part.

Energy budget-based duty cycling: In a sensor network, duty cycling mechanism depends on the harvested energy, consumed energy, and distance between nodes and data aggregator/receiver. In a traditional IoT, nodes near the sink exhaust quickly due to the additional burden of relaying the data of far-away nodes in multi-hop communication. On the other hand, in EH-IoT, nodes remain alive as long as they are receiving replenishable energy from the environment using energy harvesters. Kansal et al. [122] present duty cycling mechanisms for a single node, as well as for a sensor network, to achieve sustainable performance in EH-IoT. They describe a model for calculating the minimum size of the ESU/battery for sustainable operation of the embedded device. The duty cycle of a sensor node depends upon the average harvested as well as consumed energy in active and sleep modes. This duty cycle can be adjusted such that the overall energy consumption does not exceed the overall harvested energy. Similarly, if the harvested energy is increased, the duty cycle can also be raised to improve the performance within the given energy budget. The authors in [122] implement a duty cycling mechanism on the embedded device and demonstrate that the node has adjusted its duty cycle in accordance with the harvested energy to achieve sustainable operation in EH-IoT.

A mathematical model for duty cycling the sensor nodes according to the harvested energy is described in [123]. It achieves the ENO and maximizes the system performance by adapting the dynamics of the replenishable energy source at run-time. It employs Exponentially Weighted Moving Average (EWMA) scheme to predict the future harvested energy, which is used to compute the duty cycle of a node. Bouachir et al. [124] propose a MAC protocol for efficient energy utilization in cooperative Wireless Sensor Networks (WSNs). Their algorithm incorporates the nodes' residual energy and data requirements to schedule the active as well as sleep time periods of sensor nodes. Therefore, it minimizes the problem of early depletion of nodes near the data aggregator, which reduces the coverage hole dilemma [125]. Yang et al. [126] propose a sensing scheduling algorithm which dynamically adapts the sensing rate according to the available energy in the ESU. They also propose a mathematical model for optimal sensing scheduling in energy harvesting sensors. In contrast to the previous works [77], [127] that focus on energy allocation to the sensors, the sensing scheduling algorithm [128] optimizes the sensing epoch depending on the energy budget. The authors in [128] present the finite and infinite battery case and suggest an online scheduling policy that approaches the theoretical offline optimal scheduling mechanism. An event-driven duty cycling mechanism is proposed in [129] for power management of a road side monitoring unit. It harvests energy

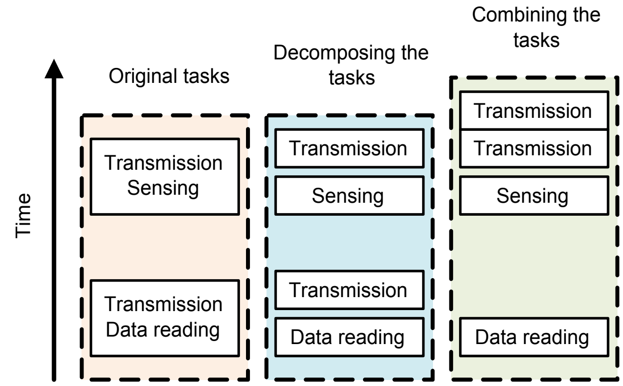

Fig. 11. Illustration of decomposition and combining of tasks to reduce the energy consumption.

from the SEH and transmits data packets according to the events of the traffic flow on the road using an Earliest Deadline First (EDF) algorithm. This implementation [129] achieves lower energy consumption and thus results in longer lifetime of the road side monitoring unit.

Predicted harvested energy-based duty cycling: In certain circumstances, the available harvested energy may not be sufficient to run an energy-intensive task on the EH-IoT sensor node. Therefore, knowledge of the future incoming energy is important to delay the tasks during energy scarcity periods until sufficient energy is available, without missing any deadline, as illustrated in Fig. 12. It shows that task 1 is executed as soon as it arrives at the node due to the higher energy availability than required for the execution of task. However, task 2 arrives when the available energy is lower than required for the execution of task. As there is a prediction of future harvested energy, the task is delayed until sufficient energy is available for its execution. In this way, the predicted harvested energy improves the energy utilization and minimizes the number of missed deadlines of tasks. Moser et al. [130] present an algorithm for task scheduling in environmentally powered IoT. To the best of our knowledge, this is the first detailed work that addresses the task scheduling problem in EH-IoT. The algorithm in [130] hesitates to execute the tasks until their deadlines and thus performs well by conserving energy for time-critical tasks that may have shorter deadlines. It computes the optimal start time of a task according to the available and predicted harvested energy. The authors in [130] evaluate their algorithm using the harvested energy from SEH and results show that it offers fewer deadline violations as compared to the previous algorithm [131]. The authors in [132] extend the work of [130] with a detailed mathematical model and consider the practical considerations in implementing the algorithm on a real embedded device. They also propose an optimal start time for the execution of tasks depending upon their deadlines, energy consumption, stored energy and future harvested energy.

Sommer et al. [133] propose a scheduling framework for various sensors (such as Global Positioning System (GPS), accelerometer, magnetometer, etc.) for perpetual tracking of flying foxes that travel long distances from their foraging

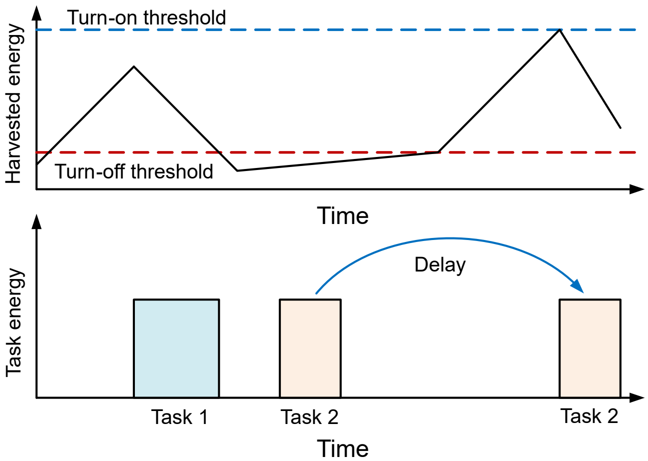

Fig. 12. Predicted harvested energy allows to delay the execution of tasks during energy scarcity periods.

camps in the search of food. The sampling rate of sensors is based on the available and the future harvested energy. The algorithm in [133] also takes into account the mobility and activity of flying foxes to trigger the next sensor sample. This technique ensures that maximum tracking accuracy is achieved within the given dynamic energy budget. Györke et al. [134] exploit the knowledge about the environment to schedule non-equidistant samples, both in time as well as in space. The predicted harvested energy is taken into account to devise a conservative sampling approach when the predicted harvested energy is low. This algorithm [134] also uses the neighbour's information in devising the duty cycle. It increases the duty cycle of nodes in the vicinity of a place where an event has occurred. The other nodes operate at their usual duty cycle to conserve energy. In the next subsection, we explore the applicability of tasks scheduling algorithms for energy harvesting-based sensors and discuss the most suitable algorithms that can be implemented on the batteryless embedded devices.

C. *Task scheduling for energy harvesting-based sensing*

In this subsection, we explore the applicability of previously discussed task scheduling algorithms for energy harvesting-based sensors. Table IV provides an overview of different studies in the literature which use one or more of task scheduling algorithms. The goal of the scheduling algorithms is to run the sensor node within the limited available energy budget to meet the deadlines of tasks, enhance the performance in terms of activity detection and to achieve ENO. Table IV comprehensively describes the state-of-the-art related to task scheduling algorithms, their performance metrics and their evaluation methods (i.e., simulation or hardware implementation). Some of the previous works employ DVFS to manage the harvested energy and schedule the tasks on the node by dynamically adjusting the voltage and frequency in EH-IoT, as discussed in detail in Section III-B1. The nodes are equipped with energy harvesters that generate energy to run the tasks, and the node switching is controlled using DVFS. Furthermore, the voltage level can be adjusted to power the active hardware module only, instead of all components of the node, to minimize the energy consumption. Secondly, larger tasks can be decomposed into smaller subtasks that consume lower energy during their operation, as described in Section III-B2. Identical tasks can be grouped together to save energy that would otherwise be consumed in repeated switching of the node's hardware. For example, instead of transmitting two data packets separately, they can be merged to save the energy required to initialize the radio transceiver. Duty cycling is another task scheduling mechanism that allows to control the consumed energy when nodes do not perform any useful operation, as discussed in Section III-B3. The nodes in EH-IoT are turned on to execute the tasks according to the harvested energy, type of the task and energy demand. This results in reduced energy consumption as nodes are switched to low energy modes during their idle time slots.

The predicted harvested energy plays an important role in scheduling the tasks on the node during energy scarcity periods. Table IV shows that there are two main approaches for considering the predicted harvested energy in the literature: devising a model for energy computation (C) or using previous available algorithms (P). Most of the previous works devise an energy prediction model, which computes the future harvested energy using the previous harvested energy samples and environmental parameters, as discussed in Section III-D in detail. Low priority tasks that require higher energy can be delayed if there is a prediction of higher harvested energy in the future. This allows to utilize the available limited harvested energy for running the high priority and low energy tasks without violating their deadlines. Another objective of scheduling algorithms is to meet tasks deadline. High priority tasks are executed ahead of low priority tasks to meet the Quality-of-Service (QoS) requirements. Depending on the application, the low priority tasks can be pre-empted during their execution, when high priority tasks arrive at the task scheduler. Finally, tasks are executed within the available energy budget to achieve ENO on the sensor node. Tasks are scheduled according to the available energy and required energy to run the tasks, as shown in Table IV. If the available energy is lower compared to the requirement of a high energy task, a low energy task is executed, even though it has lower priority, to utilize the valuable harvested energy for useful operation. As illustrated in Table IV, the task scheduling algorithms can be evaluated using two approaches: performing simulations or implementing in a real-world scenario.

Table IV portrays that most of the previous works validate their algorithms using simulations instead of real hardware implementation. The last column of Table IV shows the required difficulty level in implementing the given task scheduling algorithms on the energy harvesting-based sensing device. DVFS based algorithms are highly difficult to implement on the tiny and miniaturized sensor nodes, due to the stringent requirement of complex circuitry that provides various voltage levels for different components of the node. Similarly, the algorithms that are validated in simulations need significant effort to be implemented on the real energy harvesting-based sensor, due to different hardware design for this new class of sensors that run intermittently without conventional batteries.

TABLE IV: Summary of Task Scheduling Algorithms in EH-IoT

Year and Reference	Energy harvester	Scheduling policy: DVFS	Scheduling policy: Decomp./ Comb.	Scheduling policy: Duty cycling	Based on: Predicted energy	Based on: Deadline	Performance metric	Performance assessment	Difficulty in using it in energy harvesting based sensing
2001 [108]	General	✓					Remaining energy	Modeling	High
2004 [122]	Solar			✓			Latency	Simulation	High
2006 [123]	Solar			✓	✓(C[2])		Energy utilization	Hardware	Medium
2006 [130]	General			✓	✓(P[3])	✓	Deadline violation	Simulation	High
2007 [132]	Solar			✓	✓(C)	✓	Deadline violation	Simulation	High
2008 [109]	Solar	✓				✓	Deadline miss rate	Simulation	High
2009 [110]	Solar	✓				✓	Deadline miss rate	Simulation	High
2010 [111]	Solar	✓					Deadline miss rate	Simulation	High
2010 [112]	Solar	✓					No. of executed tasks, Average accuracy, Energy consumption	Hardware	High
2010 [135]	Water flow			✓		✓	Depleted nodes	Simulation	High
2011 [136]	Solar			✓		✓	Deadline miss rate Capacity of energy storage	Simulation	High
2011 [137]	General			✓			Average idle time Feasible task set	Simulation	High
2011 [138]	Solar			✓		✓	Battery charge level Energy violation rate	Simulation	High
2012 [117]	Solar		✓		✓(P)	✓	Number of tasks executed, missed deadlines	Hardware	Medium
2012 [113]	Solar	✓			✓(C)	✓	Deadline miss rate Minimum storage capacity	Simulation	High
2012 [139]	General			✓	✓(P)		End-to-end delay, BF, Packet delivery ratio	Simulation	High
2012 [134]	Solar			✓			Energy consumption	Simulation	High
2012 [140]	General			✓			Number of deadline violations First deadline violation	Simulation	High
2012 [141]	Solar			✓	✓(P)	✓	QoS violation count	Simulation	High
2012 [142]	Solar			✓	✓(C)		Root mean square error	Simulation	High
2013 [143]	Solar			✓		✓	Time & energy consumption	Simulation	High
2013 [144]	General			✓			Length of idle time	Simulation	High
2013 [145]	Solar			✓	✓(C)		Network lifetime	Simulation	High
2013 [114]	Solar	✓			✓(P)		Task drop rate	Simulation	High
2013 [77]	Solar			✓	✓(C)		Battery SoC	Simulation	High

[2]C: Devise a model for energy computation
[3]P: Employ previous energy prediction algorithms

Year and Reference	Energy harvester	Scheduling policy: DVFS	Scheduling policy: Decomp./ Comb.	Scheduling policy: Duty cycling	Based on: Predicted energy	Based on: Deadline	Performance metric	Performance assessment	Difficulty in using it in energy harvesting based sensing
2014 [146]	Solar			✓	✓(C)		No. of executed tasks	Simulation	High
2014 [147]	Solar			✓	✓(P)	✓	Time & energy constraint	Simulation	High
2015 [148]	Solar			✓		✓	Deadline miss rate Number of ready tasks	Simulation	High
2015 [149]	RFID reader			✓			Power consumption with time	Hardware	Medium
2015 [118]	Solar		✓		✓(P)	✓	Number of tasks executed	Simulation	High
2015 [126]	General			✓			Mean Square Error	Simulation	High
2015 [150]	General			✓	✓(P)	✓	Completed tasks	Hardware	Medium
2015 [151]	Solar			✓		✓	Deadline miss rate, Energy utilization	Hardware	Medium
2016 [115]	General	✓				✓	Average overhead Average busy period	Simulation	High
2016 [152]	Solar			✓	✓(C)	✓	Deadline success ratio	Simulation	High
2016 [119]	Solar			✓			System efficiency	Hardware	Medium
2016 [153]	General			✓		✓	Deadline miss rate, energy violation rate	Simulation Hardware	High
2016 [154]	Solar			✓			No. of sent packets, Delay	Simulation	High
2016 [155]	Solar			✓	✓(C)	✓	Deadline miss ratio, Energy utilization efficiency	Hardware	Medium
2016 [156]	General			✓			Data queue size, Energy queue size	Simulation	High
2016 [128]	General			✓			Sensing performance, Infeasible sensing epoch, Battery overflow	Simulation	High
2016 [129]	Solar			✓		✓	Power consumption, Battery lifetime	Hardware	Medium
2017 [157]	General			✓		✓	Deadline miss rate, response time	Simulation	High
2017 [124]	General			✓		✓	Harvested to consumed energy rate	Simulation	High
2017 [158]	General			✓			Energy and time overhead Energy consumption	Simulation	High
2017 [159]	General			✓			Remaining energy of node	Hardware	Medium
2018 [160]	Solar			✓			Expected reward	Simulation	High
2018 [161]	Solar			✓		✓	Energy efficiency, Execution rate	Hardware	Medium
2018 [162]	Solar			✓	✓(C)		Task completion rate	Simulation	High
2019 [133]	Solar			✓	✓(C)	✓	Average tracking error	Simulation	High

Furthermore, the algorithms that decompose and recombine tasks may not be suitable due to limited amount of harvested energy that can be used to run, at most, one atomic task at a time. On the other hand, duty cycling based scheduling mechanisms can be implemented on the energy harvesting sensors. It is due to their ease of implementation and compatibility with intermittently powered sensor nodes. However, it needs significant modifications as the energy harvester acts as a sensor and source of energy simultaneously without conventional ESU; therefore, we place them in medium difficulty level, as displayed in Table IV.

Most interestingly, none of the previous task scheduling algorithms employ energy harvesters as activity/motion sensors. All existing task scheduling algorithms employ energy harvesters as a source of power only and use conventional sensor modules for the target application, consuming significant energy during their operation. This puts further pressure on the limited available harvested energy, due to the requirement to power both the sensor as well as the processor, which reduces the overall system lifetime. Therefore, there is a potential to devise revised task scheduling algorithms that employ energy harvesters as sensors and source of energy simultaneously [25]. The objective of these task scheduling algorithms is to maximize the lifetime of sensor nodes as well as to achieve the highest performance level, using the intermittent and limited harvested energy. Interestingly, this harvested energy exhibits synchronization with the underlying activity and thus energy is harvested when an activity is performed. Later, this harvested energy can be employed as a trigger signal to sample the harvesting signal when an activity is performed, to track the change in activity. This leads towards the possibility of autonomous and self-powered EH-IoT systems, due to the elimination of sensor-related energy consumption by exploiting the embedded information in the energy harvesting signals for context detection applications.

Most of the previous task scheduling algorithms consider the predicted harvested energy, while scheduling the tasks on the sensor node. This results in maximum utilization of current and future harvested energy without missing the deadlines of tasks. In order to fully understand the functioning of the task scheduling algorithms, it is important to comprehend the energy prediction schemes as well. Most of the harvested energy prediction schemes take into account the previous harvested energy recordings to estimate the future harvested energy profile. We explore some of the harvested energy prediction schemes in the following subsection.

D. Energy prediction schemes in EH-IoT

In order to ensure ENO, the sensor node needs to consume the harvested energy in such a way that the current node operation is not affected, and the future tasks do not run out of energy. Therefore, information about the future harvested energy is important to schedule the energy consumption proactively for sustainable operation of the system. In the literature, there are various harvested energy prediction models that employ previous harvested energy samples, weather conditions and seasonal trends to compute the future harvested energy in EH-IoT. Table V comprehensively presents some of the harvested energy prediction schemes that employ statistical, probabilistic and machine learning models to predict the future harvested energy. On a normal sunny day, the harvested energy from a solar powered node is highest at noon, and decreases towards dawn and dusk, finally reaching zero at night [165], due to the non-availability of sunlight. Keeping in mind this overall pattern of SEH, the future solar harvested energy can be predicted using the previous energy pattern. Kansal et al. [163] present a harvested energy prediction model based on EWMA for solar powered IoT. Their model relies on the intuition that the harvested energy in a particular day at a given time slot is similar to that of the energy harvested in the previous days at the corresponding time slots. Therefore, the harvested energy in a particular time slot is calculated by accumulating the weighted average of harvested energy in the previous days in the same time.

TABLE V
PREVIOUS SCHEMES IN THE LITERATURE FOR PREDICTING THE HARVESTED ENERGY IN SOLAR POWERED IOT SENSOR NODE

Year	Reference	Input parameters	Method
2007	[163]	Previous samples	EWMA
2008	[164]	Previous minimum energy	Worst-case energy prediction
2009	[165]	Weather conditions from recent past samples	Weather-conditioned moving average
2010	[166]	Weather forecast	Quadratic solar power model
2011	[167]	Multiple energy harvesters	Markov model
2012	[168]	Previous energy profiles	Profile energy prediction
2016	[169]	Past observations, Current weather	Q-learning
2016	[170]	Previous energy profiles	Profile energy prediction
2016	[171]	Previous samples	Curve fitting
2019	[172]	Global horizontal irradiance	Austronomical model

The EWMA scheme awards a higher weight to the most recent energy sample and exponentially decreases the weight for the previous energy samples, in order to calculate the future harvested energy in solar powered IoT. The weight is calculated dynamically using the real previous energy traces, which provides the lowest value of prediction error. However, the model in [163] gives significant prediction error when there is a sudden change in the weather. It is due to the reason that the EWMA scheme does not take the seasonal weather trends and diurnal cycles into account. Hassan et al. [173] propose an energy prediction model for solar powered IoT, which takes into account the sudden changes in the environment. It also takes into account the seasonal and diurnal cycles of the solar energy. However, this scheme is more computationally complex as it takes multiple parameters into account and costs more energy as well as processing time, incurring delay in the system. Another scheme that considers weather conditions for predicting the harvested energy in solar powered IoT is presented in [166]. It describes a model to predict solar as well as wind harvested energy. This scheme takes the data from the weather forecast stations to predict the energy to be harvested in future time slots. However, this model is computationally complex and depends on another information source, which increases the cost of the system. Additionally, receiving weather data and processing it on an energy-constrained miniaturized sensor node hinders the execution of other time-critical tasks. Piorno et al. [165] present an energy prediction scheme for SEH which depends on EWMA and takes into account the sudden and abrupt changes in the weather conditions. They propose to use the weighting factor depending on the solar conditions of the current day relative to the previous days. Cui [162] proposes a SEH prediction scheme for sensor nodes in EH-IoT. It employs a recurrent long short term memory neural network to forecast the harvested energy. However, this is a complex method that has higher cost in terms of energy, time, memory requirement and computational resources.

Most of the previous harvested energy prediction schemes [163], [166], [173], forecast the future solar harvested energy for the next single time slot. However, occasionally, it is also important to estimate the harvested energy for future N (where $N > 1$) time slots. Moser et al. [164] present a harvested energy prediction scheme that calculates the harvested energy for future N time slots. Their scheme considers the harvested energy in previous time slots of length N. Then, the worst case harvested energy in the previous time slots is considered as the predicted energy for the future slots. However, the algorithm in [164] does not take the fast changing weather into account which results in higher prediction errors in environments with swift weather changes. It is also a pessimistic approach, as it considers the worst case harvested energy only. Cammarano et al. [168], [170] propose a prediction model using harvested energy profiles of previous days. They store different types of energy profiles (like sunny, partially sunny, cloudy, etc.) and compare the initial values of currently harvested energy with the stored energy profiles. The stored energy profile having highest correlation with the current harvested energy is considered as the predicted energy profile for the rest of the day. However, this scheme also burdens the miniaturized IoT nodes with complex computation and data storage requirements.

Ventura et al. [167] present an energy harvesting and consumption scheme for body sensor networks using a Markov model. Their scheme considers multiple types of energy harvesters and predicts the future states of nodes in terms of energy level depending on the probabilistic model based on previous energy samples. The authors in [169] propose a Q-learning based solar harvested energy prediction model using previous energy samples and current weather conditions. This results in lower prediction error than conventional EWMA. As the harvested energy from SEH depends on luminous intensity, Zou et al. [171] employ the location of sun during next time interval to predict the future harvested energy. They use piecewise least squares curve fitting with extended Kalman filter to estimate the future harvested energy using previous energy samples. Geissdoerfer et al. [172] predict the future solar harvested energy using global horizontal irradiance and solar cell's characteristics. In order to compensate for deviations from the actual values, their scheme compares the predicted harvested energy values with the previous actual harvested energy.

As we discussed, there are various energy prediction schemes for solar powered IoT, which take into account the previous harvested energy values, weather forecasts and previous energy profiles, to correctly predict the future harvested energy, as shown in Table V. However, these schemes, when implemented on the node, consume a significant amount of energy during their execution. Therefore, in addition to prediction accuracy, the cost in terms of energy and computational complexity must also be analyzed. This kind of thorough analysis can provide the real picture and will identify the scheme that provides best energy prediction results, while executing within the limited energy and computational resources.

E. Summary and insights

We comprehensively survey and analyze previous task scheduling algorithms in EH-IoT to enhance the operational lifetime of sensor nodes. These task scheduling algorithms can be broadly divided into three main categories: DVFS, decomposition and combining of tasks, and duty cycling. Most of the previous task scheduling algorithms employ predicted harvested energy to schedule their upcoming tasks. However, none of the previous algorithms employ energy harvesting-based sensing; instead they exploit conventional sensors for monitoring the desired physical parameter. It results in significant energy consumption compared to energy harvesting-based sensors as discussed in Section II. Therefore, keeping in view this new class of sensors (i.e., energy harvesting-based sensing), the previous task scheduling algorithms need to be revised to allow the sustainable operation and achieve the maximized context detection accuracy using energy harvesting-based sensing. We critically analyze the previous task scheduling algorithms and explore their applicability for energy harvesting-based sensors in the following section. In addition, we rigorously discuss the opportunities for transforming the conventional task scheduling algorithms for the emerging class of energy harvesting-based sensors.

IV. Critical Analysis of Task Scheduling Algorithms for Energy Harvesting-based Sensing

As discussed in Section III, task scheduling algorithms manage the execution of tasks to extend the lifetime of sensor nodes in a conventional EH-IoT. However, considering energy harvesting-based sensing (i.e., energy harvesters as sensors), we explore the applicability of task scheduling algorithms for this new class of sensors. Fig. 13 portrays the interaction of a task scheduler with conventional context sensors as well as energy harvesting-based sensors (single source and multi-source). There is a fundamental difference between conventional energy negative sensors and emerging energy harvesting-based sensors which are also termed as energy positive sensors [25], [26], in terms of their operation and energy consumption. Conventional sensors consume a significant amount of energy [24] while in operation (see Fig. 13(a)), whereas energy harvesting-based sensors generate energy, in addition to providing a signal that can be used for detecting the underlying activities, as depicted in Figs. 13(b) and 13(c).

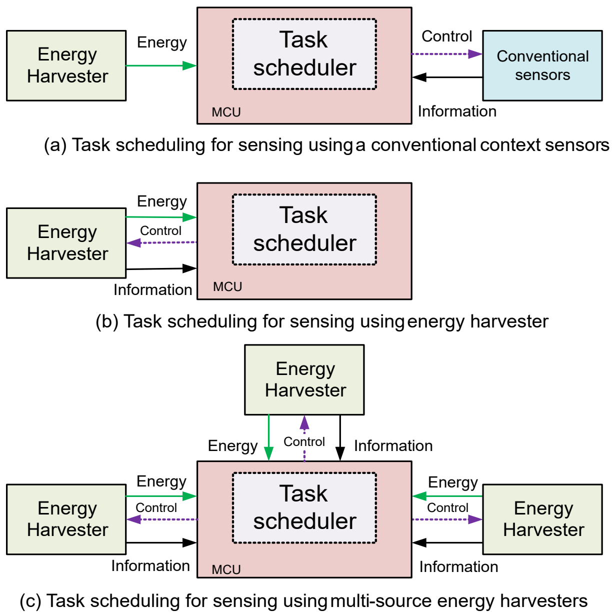

Fig. 13. Interaction of task scheduler with (a) conventional context sensors, (b) energy harvester as sensor, and (c) multi-source energy harvesters as sensors.

As energy and context information from the energy harvester are strongly correlated, sampling frequency of the harvesting signal may be reduced during stable energy/activity periods without loss of context detection accuracy. This opens new directions for designing revised task scheduling algorithms to accommodate such fundamental differences. In the following subsections, we discuss the challenges of current task scheduling algorithms and the possible solutions to formulate revised algorithms to accommodate the emerging class of energy positive sensors.

A. Challenges of existing task scheduling algorithms

Most of the existing task scheduling algorithms are complex and require a significant amount of energy during their operation on miniaturized and resource-constrained IoT sensor nodes. Decomposing and combining the tasks [117] may not be suitable for batteryless energy harvesting-based sensors due to their limited energy budget that can, at most, run one atomic task at a time. On the other hand, DVFS algorithms [108], [109] need complex hardware circuits to provide multiple voltage levels to individual hardware components of the sensor node. They may require multiple ESUs in the batteryless sensor nodes to provide various voltage levels which leads towards significant increase in energy losses, cost and form factor, and decrease in the usable energy.

Moreover, as elaborated in Section III, most of the previous task scheduling algorithms focus on enhancing the lifetime of the system at the expense of the performance in terms of context detection accuracy. In contrast, in EH-IoT the focus should be on maximizing the context detection accuracy within the available energy budget [133], as the energy is being continuously replenished. Previous task scheduling algorithms ignore the correlation between energy and context information from energy harvesters, which may help in decreasing the sampling rate of energy harvesting-based sensing, resulting in lower energy consumption compared to conventional activity sensors. In addition, current mechanisms rely on sequential functioning of program in the processor for battery-based IoT sensors, which may not be applicable for intermittent operation in batteryless sensors that experience frequent energy blackouts. Timing failure is another issue with batteryless devices that occurs when the system clock is turned off due to frequent power failures during energy scarcity periods, in contrast to conventional battery-operated IoT sensors [50] which enjoy a stable supply of power.

Devising task scheduling algorithms for multi-source energy harvesters is more challenging due to the time-varying nature of the harvested energy and the unique amount of context information from each harvesting unit. Moreover, the predicted harvested energy plays an important role in devising task scheduling algorithms, as discussed in Section III-D. However, to the best of our knowledge, there is no energy prediction algorithm for kinetic, thermal and RF harvested energy for IoT, in particular for applications which involve mobility of the transducer. There is also no existing mechanism to manage the additional harvested energy in energy positive sensors [25], [26]. Finally, most of the current task scheduling algorithms are validated through computer simulations without implementation on real hardware testbeds. Based on the comprehensive discussion of existing task scheduling algorithms in Section III and aforementioned challenges, we describe possible scheduling solutions for incorporating energy harvesting-based sensors in the following subsection.

B. Possible solutions

As discussed in Section III, the algorithms for task scheduling can be formulated to focus on both ensuring the perpetual operation of sensor nodes as well as enhancing the system's performance in terms of context detection accuracy. Among the available options, duty cycling seems to be the most appropriate choice for scheduling the tasks on miniaturized and resource-constrained IoT sensor nodes due to its inherent lower complexity and ease of implementation. However, this approach needs to be modified to adapt to the transient and intermittent operation of batteryless sensors. In addition, devising the harvested energy prediction algorithms for various energy harvesting sources including solar, kinetic, thermal and RF, can allow scheduling of tasks according to the future energy arrivals which may allow perpetual operation of sensor nodes. Moreover, it is also essential to analyze the complexity and overhead in terms of energy for running various task scheduling algorithms before implementation on real resource-constrained IoT sensor nodes.

Depending upon the type of application and nature of the environment in which energy harvesters are employed, task scheduling algorithms can be adapted in real-time. In energy harvesting-based sensing, the harvested energy may serve as a trigger signal to schedule the next sensing epoch depending on the variation in the activity and type of the application. The variation in the energy harvesting signal may be translated as a shift in the ongoing activity, using the embedded information from a couple of initial samples of the energy harvesting signal. For multi-source energy harvesters, it is important to switch between the most suitable energy harvesters depending upon the amount of context information and the harvested energy from individual transducers in real-time. This is due to the availability of distinct amounts of energy and context information from each harvester unit. According to the type of application and the underlying physical conditions, one energy harvester may offer higher context information compared to others, which needs to be tracked and scheduled in real-time. This results in enhanced context detection accuracy without consuming a significant amount of energy, e.g., via acquiring the harvesting signal at a substantially higher sampling rate or in sampling all energy harvesting signals simultaneously. In addition, a multi-source energy harvester unit can act as a reliable power source as various individual harvesters may complement each other in terms of scavenged power depending upon the environmental conditions and the physical properties of the transducers. The harvested energy from various transducers may be combined using DC-DC converters to power IoT sensor nodes. Alternatively, individual energy harvesters can be directly selected, according to the amount of generated energy, to avoid energy conversion losses [174] and enhance the usable energy.

In energy harvesting-based sensing, context information and the amount of harvested energy are correlated. Therefore, energy can be saved by reducing the sampling rate of the sensing signal during the steady state, without reducing the context detection accuracy. Moreover, the additional harvested energy can be employed to power other sensor nodes, or to opportunistically run power-intensive hardware modules on the node, such as Global Positioning System (GPS) tracker and transceiver, which leads towards the potential of fully autonomous EH-IoT. In addition, new operating systems and programming frameworks are needed for operating energy harvesting-based sensors, in order to take into account the intermittent operation of batteryless sensors, to resolve the checkpointing and timing failure issues [50], which are not present in conventional battery-based devices. Finally, there is a potential for revised and updated task scheduling algorithms for energy harvesting-based sensors, to meet the application-specific objectives, such as maximizing the sensing performance and ensuring the perpetual operation of sensor nodes in EH-IoT.

V. Future Research Directions

We discussed that energy harvesters can be employed as a simultaneous source of energy as well as context information. Since this emerging class of sensors has inherent differences compared to conventional sensors, it brings opportunities for revised energy management algorithms for the perpetual operation of EH-IoT sensor nodes. As the harvested energy is limited, task scheduling algorithms are required to execute tasks on the node according to harvested energy profile, for achieving ENO of sensor nodes in EH-IoT. There are various challenges in devising efficient task scheduling algorithms for energy harvesting-based sensors due to the varying and intermittent harvested energy that puts further constraints in case of batteryless sensors. In most of the applications, the goal of task scheduling algorithms is to enhance the activity detection performance as well to ensure the perpetual operation of sensor nodes in EH-IoT. Based on the previous discussion, future research directions for ensuring enhanced activity recognition accuracy as well as achieving ENO of sensor nodes are described in the following subsections in detail.

A. Maximum Power Point (MPP) tracking

As the output voltage and current signals of the energy harvesting transducer change due to the environmental conditions, its MPP also varies swiftly under the external stimuli. MPP tracking of KEH transducer is more challenging than solar cells, due to rapid output voltage/current fluctuations in the former compared to the relatively slow variations in the latter. Therefore, sophisticated hardware modules are required which can dynamically track its MPP at a high frequency in real-time [28]. However, it may also consume more energy in sampling the harvesting signal at a higher frequency to track its MPP voltage. Therefore, there is a potential to study the optimal MPP tracking frequency, amount of energy consumed in dynamic MPP tracking [28] and additional harvested energy, to estimate the overall gain.

B. Employing multi-source energy harvesters as a simultaneous source of energy and context information

In order to ensure the sustainable operation of sensor nodes in EH-IoT, the harvested energy should be sufficient to power the sensor hardware without the need of any external energy source (i.e., a battery). Occasionally, the harvested energy from a single energy harvester is not sufficient to continuously power each module of the sensor node. For example, SEH can not provide sufficient energy during night and darkness. On the other hand, the harvested energy from KEH is limited during lower vibrations/movements, such as sitting and standing in human activity recognition applications. Therefore, multi-source energy harvesters (e.g., SEH, KEH, TEH and RFEH) can be employed to continuously harvest higher energy as well as to extract rich activity information. The energy from these harvesters can be accumulated to power a sensor node to achieve ENO. In addition, the signals from multi-source energy harvesters can be fused to extract rich context information. For example, while KEH provides information about the movement/activity, SEH can be used to identify the indoor and outdoor environments, depending upon the amount of harvested energy, which can be employed in the localization applications. However, if a signal does not possess information about the underlying activity, its fusion with other signals may increase the cost, complexity and energy consumption of the system. In summary, there is a potential to study the amount of harvested energy and context detection accuracy using multi-source energy harvesters in various applications, such as human activity recognition, food intake detection, gait recognition and transport mode detection.

TABLE VI
COMPARISON BETWEEN HARVESTED ENERGY IN SEH AND KEH IN THE CONTEXT OF ENERGY PREDICTION

Solar energy harvesting	Kinetic energy harvesting
Periodic	Aperiodic
Relatively stable	Relatively unstable
Easily predictable	Difficult to predict
Higher energy density	Lower energy density
Easy to design the power conditioning circuit	Difficult to design the power conditioning circuit
Power is generated in the presence of light	Power is generated in the presence of vibrations
Relatively low noise in the signal	Relatively more noise in the signal
Generates DC voltage	Generates AC voltage

C. Predicting the harvested energy in EH-IoT

In contrast to SEH, the harvested energy in KEH is highly dynamic, which varies quickly according to the underlying stress/vibrations. This unstable output signal poses more challenges to devise a prediction model for the harvested energy. There is a significant difference between the energy pattern in SEH and KEH, as listed in Table VI. The harvested energy in SEH is predictable due to its overall known pattern as described in Section III-D. However, in contrast to SEH, the harvested energy in KEH can not be predicted by merely accumulating the previous weighted energy samples, as in EWMA [163], especially for long term energy predictions. The harvested energy pattern in KEH based IoT depends upon the type of application which demands dedicated models for harvested energy prediction for each use case. If the target application is human activity recognition, the KEH energy is non-identical in various types of activities [24], including walking, standing, running, going upstairs/downstairs, etc. Similarly, if the target application is transport mode detection [22], the harvested energy depends on the mode of transportation. Furthermore, in contrast to static SEH applications (except [133]), KEH is typically deployed in mobile scenarios, and has various states in most of the context detection applications, including human activity recognition and transport mode detection. Therefore, in order to predict the harvested energy in KEH, the mobility of the energy harvester must be taken into account to achieve higher prediction accuracy. Similarly, dedicated energy prediction algorithms are required for other energy harvesters, such as TEH and RFEH to estimate the harvested energy for efficient execution of tasks on the node.

The predicted harvested energy plays an important role in scheduling the tasks in EH-IoT. As the capacity of ESU is limited (due to small-sized capacitors/batteries), the harvested energy can overflow if the stored energy is not consumed in executing the tasks beforehand, which results in the wastage of resources. For example, when the battery is fully charged, there is no room to store the incoming harvested energy, which results in energy wastage, if it is not properly utilized. The solution is to utilize maximum energy, when the ESU is charged to its capacity as well as there is a prediction of future harvested energy. It results in the efficient employment of resources and maximum utilization of energy in executing the tasks within their deadlines. Similarly, if the ESU is depleted, the tasks can be delayed, according to the predicted energy, to atleast achieve a required minimum performance level.

D. Batteryless EH-IoT

Conventional EH-IoT sensor nodes employ batteries to store the harvested energy from the ambient environment and to power the embedded device. However, batteries are costly, bulky, offer a limited lifetime and are hazardous for the environment due to chemical leakage [12]. A promising solution is to employ capacitors to store the harvested energy which reduces the form factor, cost and weight of the miniaturized IoT sensor nodes. As capacitors generally have higher current leakage and lower energy storage capacity compared to batteries [175], task scheduling with a capacitor-based ESU is more challenging than for its battery-based counterpart. Intermittently charged capacitors restrict the continuous utilization of energy, which further limits the frequent execution of tasks on the node. Furthermore, the stored energy in a tiny capacitor can only be used to execute one atomic task at a given time instant [119]. While task scheduling for battery-based EH-IoT is well explored in the literature (as elaborated in Section III), there are only few works that explore and implement task scheduling algorithms for intermittently-powered batteryless IoT sensor nodes [176]. Therefore, there is a potential for new research into task scheduling algorithms that take into account the intermittent operation of nodes due to varying levels of ambient energy available in the environment, e.g., solar, thermal, kinetic and RF, to enable the autonomous operation of batteryless sensor nodes in EH-IoT. Furthermore, the use of energy harvesters as a simultaneous source of energy and context information also needs to be explored, as it reduces the energy consumption, which may offer perpetual and autonomous operation of batteryless EH-IoT without human intervention.

E. Embedded machine learning

There are several previous works [177]–[181] that implement machine learning algorithms on the IoT devices to recognize a physical phenomenon or an underlying activity. This mechanism of embedded machine learning not only reduces the transmission power consumption compared to raw data transmission [182], but also improves application latency and user privacy [26]. However, the current trend is to design and implement batteryless IoT sensor nodes [12] to minimize the environmental issues due to chemical leakage of batteries and reduce the maintenance cost of the devices. As a result, it is challenging to implement machine learning algorithms on these resource constrained sensor nodes, with unreliable and intermittently available harvested energy. This dilemma becomes more arduous with the use of a capacitor [183] (instead of a battery) which stores a minuscule amount of energy that may not warrant the execution of more than one atomic task at any particular time interval. To the best of our knowledge, there are only few works [182], [183] that implement machine learning algorithms on intermittently-powered

EH-IoT sensor nodes due to the underlying challenges related to lower energy budget, unreliable harvested energy and frequent energy blackout periods. Furthermore, as illustrated in Section IV, there are inherent differences in conventional energy negative sensing and emerging energy positive sensing. Therefore, implementing machine learning algorithms on the IoT device using energy harvesters as simultaneous source of energy and context information is another open question for the research community that needs to be addressed to ensure the perpetual and autonomous operation of EH-IoT sensor nodes.

VI. Conclusion

Energy harvesters are employed to power conventional sensor nodes in EH-IoT, eliminating the need for manual replacement and recharging of batteries that hinder their widespread adaptability and pervasive deployment. In addition to energy generation, recently energy harvesters have been used as sensors for context detection. This saves significant energy that would otherwise be used to power conventional activity sensors. Using energy harvester as a simultaneous source of energy and context information enables *energy positive sensing*, which harvest higher energy than required for signal acquisition in context detection applications. However, the generated energy from miniaturized energy harvesters is still insufficient to allow the perpetual operation of sensor nodes in EH-IoT. In order to ensure the sustainable operation of sensor nodes, the precious harvested energy needs to be consumed very efficiently for running the operational tasks on the nodes. In this survey paper, we comprehensively analyze the previous task scheduling based energy management algorithms for EH-IoT sensors. We critically analyze the challenges in incorporating the emerging class of energy harvesting-based sensors in the conventional task scheduling algorithms. Based on the extensive study of the literature, we rigorously review the need for revised task scheduling algorithms for batteryless energy positive sensors and provide potential solutions using multi-source energy harvesters. Finally, we present future research directions such as MPP tracking, employing multi-source energy harvesters, predicting the harvested energy and exploiting batteryless sensors, towards the goal of enabling the sustainable and autonomous operation of self-powered batteryless sensor nodes in EH-IoT.

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