Information-Aware Sensing Framework for Long-Lasting IoT Sensors in Greenhouse

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***Abstract*—A sensor network is an underpinning infrastructure that enables various future IoT applications, such as precision agriculture, smart farm, and greenhouse monitoring. However, these sensor devices often suffer from short-lived battery lifetime that incurs frequent maintenance operation. Although there have been a few attempts to smartly reduce the power consumption associated with communication tasks of the sensors, very few have addressed the power consumption of sensing tasks. In light of this shortcoming, we propose an information-aware sensing framework that adaptively adjusts the sensing interval for energy-saving operations based on the learned behavior of the sensor data. To prove the effectiveness of the proposed framework, we have deployed four BLE beacons equipped with luminosity and temperature sensors to collect real-life data from a desert greenhouse, which is then used to train and evaluate our proposed framework. Additionally, we have implemented the proposed framework on a commodity BLE beacon device to validate the energy-saving performance of the proposed framework. The results demonstrate that the proposed framework can effectively reduce the energy consumption involved in sensing tasks by 30% and extend the battery lifetime by up to 75%.**

***Index Terms*—Sustainable IoT, greenhouse monitoring, on-device machine learning, and BLE beacons.**

I. Introduction

The advancement of wireless communications technologies and the subsequent emergence of the new paradigm, the Internet of Things (IoT), have completely innovated the social interactions between people. In this context, the Bluetooth Low Energy (BLE) beacon is a prospected technology to enable various IoT and smart city applications such as proximity interaction, contact tracing [1], sensing, and smart agriculture [2]. However, BLE beacons suffer from short battery lifetime which induces periodic maintenance operation [3]. In the case of a BLE beacon with additional sensing hardware, the battery lifetime and maintenance issue is further amplified. A typical gas sensor, an essential hardware component to support various smart home/building applications, is often very power-demanding. For example, a typical CO_2 sensor can consume 175 mA peak current during sensing [4]. Although a low-power operation mode decreases the sensor current to 0.4 mA, the consumption is still huge compared to that required for BLE operations, which will not exceed 0.2 mA. Another example is a soil moisture sensor for smart agriculture and greenhouse monitoring application. As reported in [5], a soil moisture sensor can easily consume over 100 mA of current.

To address the battery lifetime issue, many attempts were made to minimize the power consumption of the sensor device from both hardware and software perspectives. From a hardware perspective, more energy-efficient sensing devices have been developed, such as chemiresistive sensors [6], optical gas sensors [7], and acoustic gas sensors [8]. On the other hand, there have been many attempts to reduce the power consumption associated with communication and enable self-sustainable operation, such as sleep-awake scheduling [9], and relay selection algorithm [10]. However, few attempts were made to reduce the energy consumption associated with the sensing task.

In this paper, we propose a novel machine learning-driven framework that learns the behavior of the sensor data to adaptively extend the sensing interval. By doing so, the framework can reduce the energy consumption of the sensing task when there is little to no change in the collected sensor information. To achieve this, we first propose a sensor information model that characterizes the behavior of the sensing environment based on how likely the sensor measurement is to change. The processed sensor information is then fed into a neural network for prediction. Based on the output of the neural network, the sensing interval is extended to extend the lifetime. Our novelties and contributions are summarized below:

1) proposed a novel information-aware sensing framework that leverages machine learning techniques to adaptively extend the sensing interval;
2) formulated a sensor information model that correlates the sensing interval with the amount of information; and
3) proved the effectiveness of the proposed framework through implementation/prototype using commodity BLE chipset and experiments with data collected through real-life deployment.

The rest of this paper is organized as follows. Section II presents the background information on BLE beacons and the power consumption model. Section III presents an overview of the proposed framework and details the role and design of individual components. Section IV presents experimental results with a working prototype to validate the proposed firmware. Finally, Section V concludes the paper.

II. BACKGROUNDS & RELATED WORKS

Following section presents background knowledge on BLE beacon energy consumption behavior and related works on energy-saving firmware and algorithm design. Also, related works on time-series prediction are presented to highlight the novelty of the proposed approach.

A. BLE Beacon and its Power Consumption Model

BLE beacon is a battery-powered electronic device that broadcasts short advertisement packets. A BLE beacon wakes up after every advertising interval, T_a, and sensing interval, T_σ, to broadcast its advertisement packet and make sensor measurements respectively. Otherwise, it stays in an idle state to minimize power consumption. Based on this behavior, the average power consumption of a beacon, $P_b(T_a, T_\sigma) \in \mathbb{R}_+$, can be modeled as follows:

$$P_b(T_\sigma, T_a) = \frac{E_\sigma}{T_\sigma} + \frac{E_a}{T_a} + P_i \tag{1}$$

where $T_\sigma \in \mathbb{R}_{>0}$ is the time interval between sensing tasks which is bounded between $T_\sigma^{\min} \leq T_\sigma \leq T_\sigma^{\max}$ which represents hardware limitation and application requirements for the sensing interval, $T_a \in \mathbb{R}_{>0}$, is the time interval between advertising events (in seconds) which is bounded between $T_a^{\min} \leq T_a \leq T_a^{\max}$, $T_a^{\max} = 10$ seconds and $T_a^{\min} = 0.1$ second are the upper and lower bounds of the advertising interval specified by Bluetooth specification, $E_\sigma \in \mathbb{R}_{>0}$ is the energy consumption during the sensing task, $E_a \in \mathbb{R}_{>0}$ is the energy consumption during the advertisement event, and $P_i \in \mathbb{R}_{>0}$ is the average power consumption during the idle state of the beacon.

Based on beacon's power consumption, $P_b(T_\sigma, T_a)$, its lifetime, $t_l \in \mathbb{R}_{\geq 0}$, is given by:

$$t_l = \frac{E_b}{P_b(T_a, T_\sigma) + P_m} \tag{2}$$

where $E_b \in \mathbb{R}_{\geq 0}$ is energy available in a battery or a rechargeable energy storage device, $P_b(T_\sigma, T_a)$ is the power consumption of the beacon device including advertising and sensing tasks, and $P_m \in \mathbb{R}_{\geq 0}$ is the power consumption of machine learning tasks for predicting the portion of changes.

III. OVERVIEW OF THE INFORMATION-AWARE SENSING FRAMEWORK

Here, we propose a novel sensor information-aware framework where the sensing interval of an IoT device is extended adaptively based on the learned nature of the sensing data in the predefined environment. For example, a luminosity sensor may adopt extended sensing intervals during nighttime when the changes in luminosity are unlikely. Fig. 2 shows examples of different sensor data, namely luminosity and temperature, and the corresponding portion of changes (defined in Section III-A). It can be seen from Fig. 2 (a) and (b) that the changes in the sensor information are more likely to happen during the daytime. An overview of the proposed framework is shown in Fig. 1. The framework is composed of three main components:

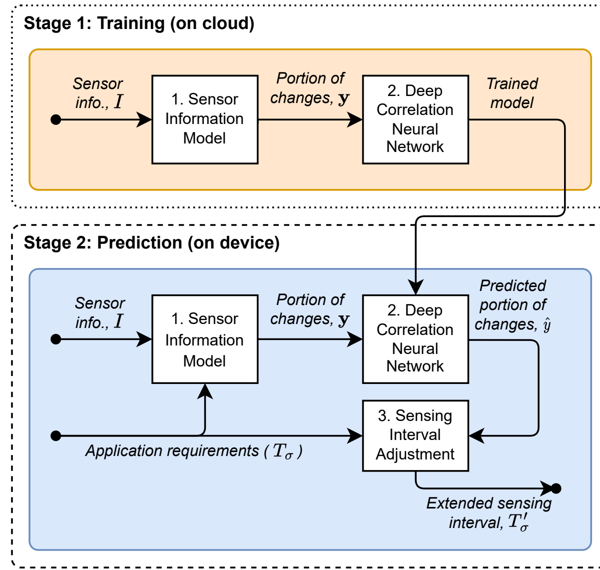

Fig. 1. Overview of the proposed sensor information-aware framework.

1) information model, 2) machine learning (ML) model, and 3) sensing interval adjustment.

Firstly, the information model is used to derive the portion of changes of the sensor data, or the probability of the sensor measurements changing. For example, an extremely low portion of changes implies that the sensor measurements are not changing, therefore a longer sensing interval should be used. The second component, the ML model, is employed to accurately and efficiently predict the future portion of changes of the sensor measurements. The machine learning model is first trained on the cloud with the portion of changes data and then the pre-trained model is deployed on the IoT device. The third component, sensing interval adjustment, is designed to calculate the sensing interval that will balance the amount of useful sensor information and the energy consumption associated with the sensing tasks based on the predicted portion of changes provided by the ML model. The method to adjust the sensing interval depends on the application requirements and the nature of the sensing tasks.

Recalling our previous example with the luminosity sensor, it would be extremely energy-efficient to employ a longer sensing interval during the nighttime at a cost of information loss. Therefore, the impact of a longer sensing interval on the amount of sensed information must be investigated such as to determine an appropriate sensing interval that will upkeep the high quality of sensed data while minimizing power consumption.

A. Sensor Information Model

To this end, we first propose the sensor information model to measure the amount of useful information in sensor data. We first define a set of information, $I = \{i_1, i_2, \ldots, i_N\}$, which is a set of information samples, which refers to the individual sensor measurements. On the other hand, a set of information changes I_c, which is a subset of I, i.e., $I_c \subseteq I$, includes all sensor information samples that indicate the changes in the

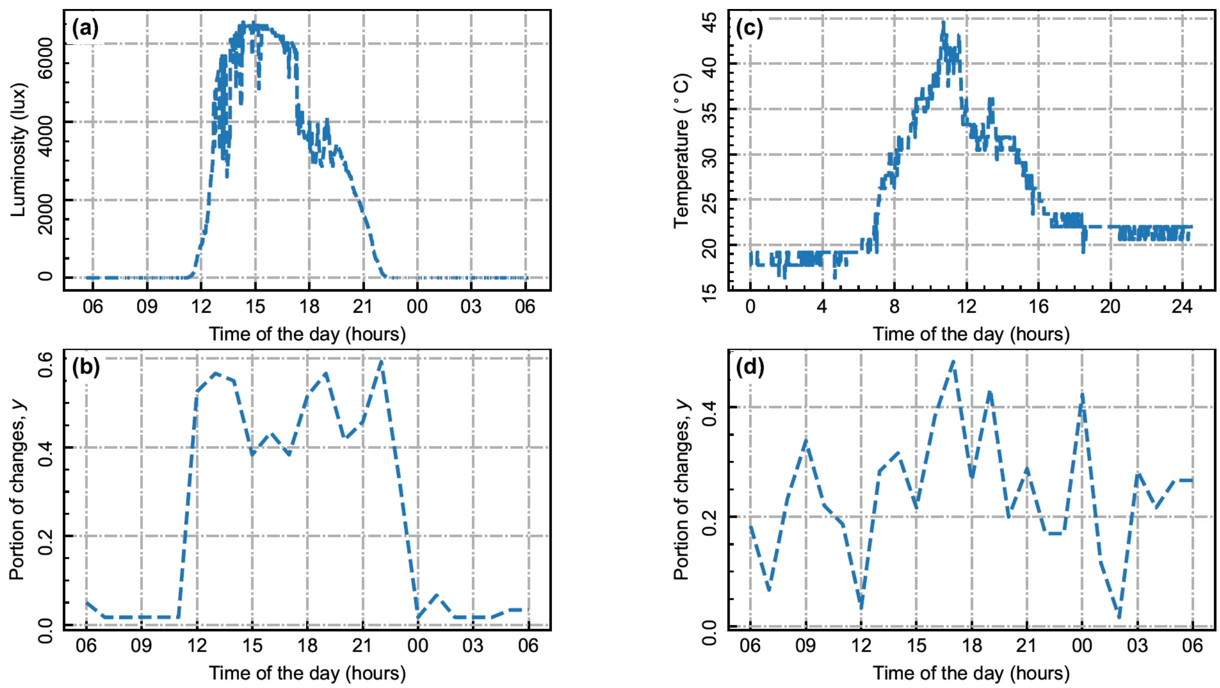

Fig. 2. Sensor measurements of luminosity and temperature data displaying varying portion of changes for different time of the day: a) luminosity; b) corresponding portion of changes for luminosity; c) temperature data; and d) corresponding portion of changes for temperature.

sensor data. It is to be noted that the set of information is slotted based on a given sensing interval.

The information collected, I, collected over collection time, T_c, can be defined as $I = \{i_1, i_2, \ldots, i_N\}$ where $i_j \in \mathbb{R}$ is a sensor measurement made during timeslot j, and N is the total number of the information samples in set I. Based on the previous formulation of I, and I_c, the amount of information, $|I|$, can also be derived. The amount of information depends on two factors: firstly, the sensing interval, T_σ, and secondly, the collection time for the sensor data, $T_c \in \mathbb{R}_{>0}$. Therefore, the amount of information, $|I|$, can be formulated in terms of T_σ and T_c as:

$$|I| = \left\lfloor \frac{T_c}{T_\sigma} \right\rfloor \tag{3}$$

where the amount of information, $|I|$, is a natural number, $\mathbb{N}_{\geq 0}$, $T_\sigma \in \mathbb{R}_{\geq 0}$ is the sensing interval which is bounded between $T_\sigma^{\min}$ and $T_\sigma^{\max}$, i.e., $T_\sigma^{\min} \leq T_\sigma \leq T_\sigma^{\max}$, $T_\sigma^{\min} \in \mathbb{R}_{\geq 0}$ is the minimum sensing interval that can be supported by the sensor device reflecting the physical limitations of a given hardware, and $T_\sigma^{\max} \in \mathbb{R}_{>0}$ is the maximum sensing interval that is specified due to application requirements in order to secure a minimum sensing performance. It should be noted that $T_c \geq T_\sigma$ in order to get at least one information sample. A floor function is used to ensure the amount of information, $|I|$, is a natural number.

However, the information, I, may contain multiple redundant information samples that incur extra energy costs for insignificant information. For example, a luminosity sensor is highly likely to measure the same values near 0 lux during a night time as shown in Fig. 2 (a). Therefore, it would be ideal to sense only non-redundant information or information changes, I_c, which indicate changes in the sensor measurement. In order for a sensor measurement to indicate a change, it must be different from the previous samples indicating a change in the environment being monitored. For example, given a sequence of temperature sensor samples, {**23**, 23, **25**, 25, **23**, 23}, the first, third and fifth information samples (shown in bold) indicate that the sensor samples are different from the previous information samples, and are considered as information changes. Therefore, elements of I_c must satisfy the condition $i_j \neq i_{j-1}$. Based on these characteristics, the information changes, I_c, is formulated as:

$$I_c = \{i_j \in I \mid i_j \neq i_{j-1}\} \cup \{i_1\} \tag{4}$$

where the index of the information sample, $j = \{2, 3, \cdots, N\}$, ensures that the first information sample is not considered. It should be noted that i_1 is always an element of I_c since it is the first sensor measurement and therefore will be unique.

The portion of information changes, y, which indicates how likely the sensor data is to change, can be given by the formulation below:

$$y = \frac{|I_c|}{|I|} \tag{5}$$

where the portion of changes, $y \in (0, 1]$, indicates a number of information changes collected. The portion of changes, y, is given by the amount of information changes, $|I_c|$, divided by the amount of raw information, $|I|$. The calculated portion of change, y, is used in the next section for generating the predicted portion of changes.

Based on Eq. (5), the collected sensor data were converted to a portion of changes data based on the proposed information model. To compute the portion of changes, the sensor data

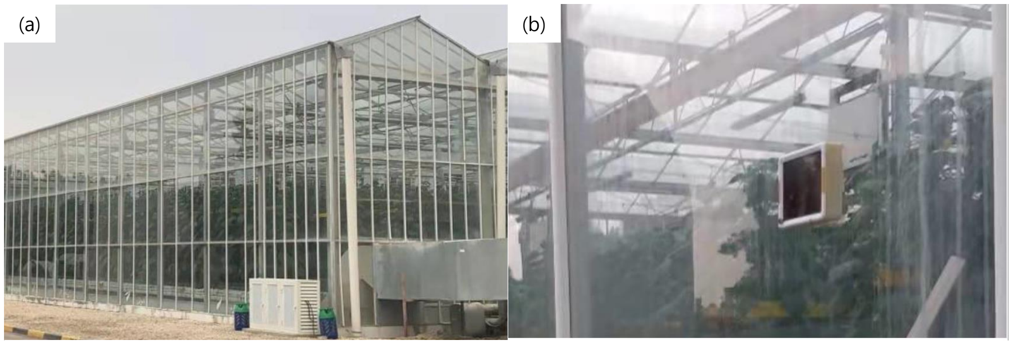

Fig. 3. Real-life data collection location and setup using luXsensing beacon for experiments and validation: (a) desert greenhouse in Qatar; (b) luXsensing beacon deployed inside the greenhouse.

are first slotted by every hour, i.e., $T_c = 1$ hour. The hourly slotted sensor data are then processed to generate the number of information of changes. Then the portion of changes, y, is computed. Fig. 2 (c) and (d) shows the portion of changes computed for temperature and luminosity data. It can be observed that the portion of changes behaves as expected: portions of changes are close to 0 during night time and exhibit higher values during day time. The portions of changes are then fed into the neural network to generate the predicted portion of changes, $\hat{y}$. In this paper, deep correlation neural network [11] is employed to generate the predictions.

B. Extended Sensing Interval

Based on the predicted portion of changes, $\hat{y}$, a sensing interval can be adjusted to minimize energy consumption while maximizing the amount of information. High $\hat{y}$ indicates a fast-changing sensor output, and therefore the sensing interval should be small to ensure enough transient information is collected. Consequently, an extended sensing interval, T'_σ should be inversely proportional to $\hat{y}$. Based on this observation, the extended sensing interval, $T'_\sigma \in \mathbb{R}_+$, can be given by:

$$T'_\sigma = \frac{T_\sigma}{\hat{y}} \tag{6}$$

where T_σ is the original sensing interval used for the sensing task, and $\hat{y} \in (0, 1]$ is the predicted portion of changes. However, due to the design of the working mechanism of neural networks, the proposed neural network may often generate 0 values for the predicted portion of changes, $\hat{y}$. To ensure that the predicted portion of changes, $\hat{y}$, conforms to its proper intervals, it is offsetted by a small value of 0.01 and then scaled to fit between the range of 0.01 and 1. It should be noted that, similar to T_σ, the extended sensing interval, T'_σ is also bounded between $T_\sigma^{\min}$ and $T_\sigma^{\max}$, i.e., $T_\sigma^{\min} \leq T'_\sigma \leq T_\sigma^{\max}$. Therefore, any adjustment that exceeds these bounds is mapped to either $T_\sigma^{\min}$ or $T_\sigma^{\max}$.

IV. Experiments & Results

The following section aims to demonstrate the effectiveness of the proposed framework. The proposed framework will be evaluated in 3 aspects: 1) neural network energy consumption; 2) accuracy of the collected sensor information using the extended sensing interval, T'_σ; and 3) lifetime extension. Through the experiments, we not only prove the superiority of the proposed framework but also attempt to deepen our understanding by examining and discussing interesting behaviors of the framework. In these simulation experiments, we employed the real-life sensor data that we collected in the desert greenhouse in Qatar.

TABLE I
Summary of the Luminosity and Temperature Sensor Dataset collected in the Desert Greenhouse Located in Qatar.

Data Type	Luminosity and temperature
Temporal Duration	Jan. 17 - Feb. 25, 2022 (40 days)
Location	Ash-Shahaniyah, Qatar (desert greenhouse)
# of Sensing Devices	4 units
Sensing Interval, T_σ	1 min (default)

A. Data Collection & Pre-processing

To validate our proposed framework, we have collected real-life sensor data, namely luminosity, and temperature, with luXsensing beacons deployed in a desert greenhouse located in Qatar. luXsensing beacon is an energy harvesting BLE beacon hardware that we have developed and prototyped to collect temperature and luminosity sensor data. The greenhouse has an area of 2,500 m^2 and a height of 8 m covered entirely in silica glass. Details of the dataset are presented in Table. I.

B. Neural Network Energy Consumption

In order to prove the energy efficiency of the proposed framework, the deep correlation neural network [11] was implemented on a commercial BLE beacon chipset, nRF52832 chipset, which is equipped with 64 MHz ARM Cortex-M4 CPU. The nRF52832 chipset is also equipped with a floating point unit that allows various floating point operations. The implementation of our proposed neural network for nRF52832 chipset can be found on our GitHub page[1]. Based on this implementation, computation time and energy cost were measured. Table II shows that the DCAN requires 12559 FLOPS,

[1]https://github.com/sbeacon/Task-aware-Framework-using-Machine-Learning-for-Long-lasting-Green-IoT-Sensing-Devices

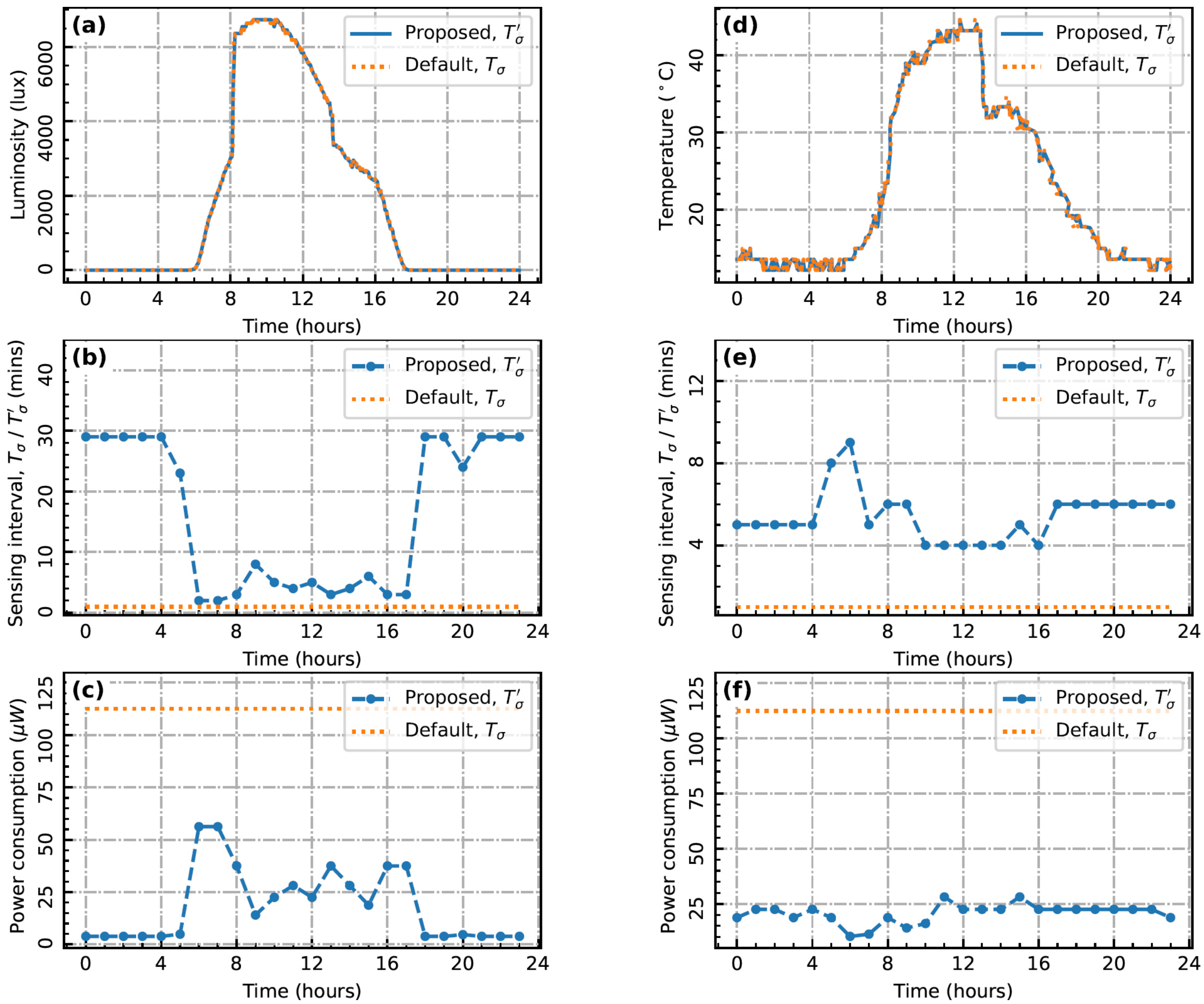

Fig. 4. Sensor data are accurately collected with the proposed extended sensing interval, T'_σ, compared to sensor data collected with static default sensing interval, T_σ, and helps to reduce the sensing-task related power consumption significantly: a) luminosity; b) corresponding T'_σ; c) corresponding power consumption; d) temperature data; e) corresponding T'_σ; and f) corresponding power consumption.

TABLE II
COMPUTATION TIME AND ENERGY COST OF THE NEURAL NETWORK IMPLEMENTED ON THE BLE BEACON CHIPSET.

	FLOPS (#)	**Clock Cycles** (#)	**Computation Time** (ms)	**Energy** (mJ)
DCAN	12.6k	1,085k	16.97	0.214

which is indeed manageable for an off-the-shelf BLE beacon chipset and consumes a very small amount of energy.

C. Sensor Information Accuracy

Based on the predicted portion of changes generated by the proposed oracle-interpreter neural network, we can now calculate the extended sensing interval, T'_σ, as shown in Eq. (6). However, one of the major concerns of extending the sensing interval is the loss of important information. To address this concern, simulation results of the collected sensor information are presented in Fig. 4 (a) and (d). The simulation generates a sequence of sensor information samples that would have been collected with a given sensing interval, namely, the extended sensing interval, T'_σ, and the default sensing interval, T_σ, which is used originally by the application. During the experiments, a default sensing interval, T_σ, of 1 minute was employed, since this was the default sensing interval originally used in the greenhouse application.

It can be seen from Fig. 4 (a) and (d) that the proposed extended sensing interval, T'_σ, can accurately regenerate the sensor information, and the collected sensor information is almost equivalent to that using the default sensing interval, T_σ. Fig. 4 (b) and (e) shows the extended sensing interval, T'_σ, used to collect the sensor information shown in Fig. 4 (a) and (d). It can be observed from Fig 4 (b) that during the night time when the portion of changes, y, is low, the extended sensing interval is relaxed to save energy. The stored energy is put to better usage during day time.

The power saving benefits of the proposed framework are better reflected in Fig. 4 (c) and (f), which show the power

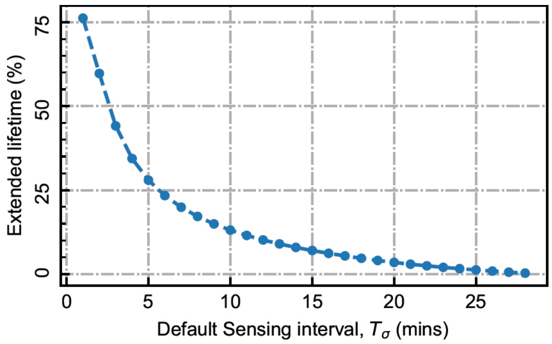

Fig. 5. The proposed framework can extend the lifetime up to 75% compared to that of the traditional method.

consumption of the sensor device operating with the proposed extended sensing interval, T'_σ, and the default sensing interval, T_σ, of the original application. It can be observed from Fig. 4 (c) when the extended sensing interval, T'_σ, is relaxed, the power consumption can be reduced close to less than 10 μW. The power consumption reduction benefited from the extended sensing interval is very significant when compared with the power consumption using the default sensing interval, T_σ, which is around 120 μW.

Although the effect and changes of extended sensing interval, T'_σ, for the luminosity dataset are clear and noticeable, that of the temperature dataset is more subtle. It can be observed from Fig. 4, the extended sensing interval, T'_σ, will slightly decrease during the daytime, but will not be greatly relaxed. This is due to the noisy nature of the temperature dataset, due to which the portion of changes values remained relatively unchanged throughout the entire dataset. Therefore, a precise adjustment of the sensing interval was not feasible. In the future, such noisy characteristics may be corrected by the sensor information model, which may calculate the portion of changes based on a threshold or rate of changes.

D. Lifetime Extension

Based on the predicted portion of changes, $\hat{y}$, the extended sensing interval, T'_σ, and corresponding power consumption, the lifetime of the sensing device can be calculated. During the entire scope of the experiments, we have assumed that the sensing task will consume around 500 mA of current for approximately 7.5 ms, and Bluetooth advertising task will operate with a fixed advertising interval of 1 second and therefore will consume around 20 μA of current. We also assume that the voltage source is stable at 1.8 V.

Fig. 5 shows the extended lifetime of a sensing device equipped with a 1000 mAh battery. It can be seen that the proposed framework extends the lifetime significantly by about 75%. It can also be observed that when a very long default sensing interval, T_σ, is employed, the lifetime gain of the proposed framework is insignificant. This is because at such a low requirement, the power consumption of sensing tasks becomes extremely insignificant. Hence, the lifetime is dictated by the power consumption of broadcasting tasks, leading to marginal energy saving with sensing tasks. Moreover, since both the extended sensing interval, T'_σ, and the default sensing interval, T_σ, share the same upper bound, $T_\sigma^{\max}$, the power consumption of the two intervals will converge as default sensing interval, T_σ, approaches $T_\sigma^{\max}$, and so will the lifetime.

V. Conclusion

This paper proposed a novel sensor information-aware framework that learns sensor information behavior and adjusts the sensing interval, T_σ, to maximize the lifetime of a sensor device while still collecting accurate sensor information. To verify the proposed framework, we have developed, prototyped, and deployed 4 units of luXsensing beacon and collected luminosity and temperature datasets at a desert greenhouse located in Qatar. Comprehensive experiments based on the real-life dataset are conducted to demonstrate that the proposed framework can achieve extremely low prediction errors. Furthermore, we have implemented a neural network on a commercial BLE chipset, nRF52832, to prove the energy efficiency of the proposed network. Based on this implementation, we have verified that the proposed framework was able to extend the lifetime of the sensing device up to 75%.

For future work, the proposed framework can be tested with other types of sensor data which may not be necessarily periodic like temperature and luminosity data used in this paper. Investigations regarding optimal values of collection time, T_c, and its effect on lifetime performance can be investigated. Moreover, it can be applied to other power-constrained IoT devices besides BLE beacons such as LoRa-enabled sensor devices.

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