Surrogate model-based energy-efficient scheduling for LPWA-based environmental monitoring systems

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ABSTRACT The rapid development of the Internet of Things (IoTs) with newly proposed wireless communication technology has compactly generated connections between humans and the physical world. Beginning with research on wireless sensor networks (WSNs), environmental monitoring research has currently developed into wider applications aiming to detect the world with multitudinous IoT technologies. Recently, Low Power Wide Area (LPWA) technologies have provided such benefits as longer communication range, larger network capacity, and low unit-price, providing more choices for managers to set up more detailed monitoring. However, the operational lives of battery-powered end-devices still hinder long-term monitoring. In this paper, we propose a decentralized framework for energy-efficient environmental monitoring considering both the operation cost and current computational capabilities of the end-devices. The core function is a low-complexity scheduling approach that can balance the monitoring performance and energy consumption for different environmental states. Driven by the prediction accuracy of the surrogate model, monitoring nodes are selected. Meanwhile, the energy consumption of the other nodes is saved. Simulation results demonstrate that the proposed monitoring system has high energy efficiency with acceptable performance. The battery life of the whole system can be prolonged by up to 136.22%.

INDEX TERMS environmental monitoring, Internet of Things, low power wide area, surrogate model

I. INTRODUCTION
The prosperous growth of the Internet of Things (IoTs) has deeply influenced our lives. Connections among things are initiated, suggesting that an amazing future is ahead. One of these connections is between human lives and the environment. By detecting environmental information, an IoT-based environmental monitoring system can help us better understand and manage the environment.

In early research, wireless sensor networks (WSNs) are proposed as the connection tools between machines and the environment [1]. In state-of-the-art work, the length of the IoT communication range, especially Low Power Wide Area (LPWA) technology, has significantly enlarged the monitoring scale and enhanced the mobility of end-devices. Thus, traditional communication range limitations in WSNs are not obstructions for these newly proposed IoT technologies [2]. Meanwhile, the low unit-price and the miniaturized LPWA end-devices also provide possibilities to widely apply WSNs. Hence, the scale of the IoT systems can be enlarged to an unprecedentedly large size but with affordable prices [3].

However, one bottleneck of the LPWAs’ application is how to better use batteries with a limited capacity for long-term operation [4]. Two main categories of designs or approaches have been proposed to enhance the battery life of the IoT nodes.

One category is the self-powered way where the devices obtain energy from the environment through multiple ways, such as solar-powered batteries, piezoelectric materials for harvesting vibration energy, thermo-electric cells, and...
energy harvesting antennas [5-7]. However, these energy harvesting methods are designed for unique environments with less universality. For instance, solar-powered devices are operated outdoors with rich sunlight, rather than indoors [7]. Additionally, the higher cost and larger size of self-powered designs limit their application. Energy harvesting methods are more suitable for middleware devices, such as gateways or communication relays, rather than end-devices.

Another approach seeks to save energy during operation, such as energy management circle designs and energy-aware protocols. Essentially, these inexpensive circles with low power designs are the cornerstone of IoT systems. The designs are the main evidence of the ultra-long operation lives in many whitepapers [8]-[10]. Moreover, a majority of IoT companies and organizations have promoted their devices to be major components of the IoT network based on their particular circles and sufficiently simple protocols [9], [10].

Meanwhile, protocol researchers develop multiple ways to decrease energy consumption during the communication. Certain researchers seek to combine traditional technologies with new IoTs to achieve better performance and save more energy. For example, a WSN-assisted IoT network has been proposed with an efficient centroid-based routing protocol. Based on the virtue of the base station and the IoT network, the protocol utilized several algorithms to enhance energy efficiency during transmission [11]. Several other state-of-the-art studies showed more interest in independent applications. For instance, in [12], the authors proposed a cooperative radio resource management scheme in the NB-IoT system to improve the transmission rate while reducing energy consumption. This cooperative scheme efficiently employed the restricted resources to support massive IoT devices and partly considered the computation complexity.

Though many approaches have been proposed to prolong the operational lives of IoT devices, most solutions for the energy problem do not consider system cost or construction investment. That property is in conflict with the initial vision and the IoT promotion reasons. In addition, the cooperative scheme in [12] shows a relatively high computation complexity, raising the initial system investment. The complex protocols could increase the unit-price of each node, which is counter to promoting the technology. Thus, energy-efficient methods are required with low computational complexity in the current IoT-based system.

In this paper, the main idea is derived from past WSN research that controls the node during long-term operation. These relative approaches have solved the energy problem from the system operation scheduling, such as wake-up, mobile node, and relay scheduling [13]-[15]. The existing scheduling approaches seek to solve the energy problem through a balance between operation and sleeping time [15]. It remains a challenging problem to schedule node activities for the reduction of energy consumption [16]. However, traditional WSN scheduling approaches could not adapt the scale of the massive and ever-increasing IoT devices, considering different operational constraints.

Several IoT researchers have performed similar scheduling works to guarantee long-term network performance. For example, Zhai et al. [17] formulated the energy problem for massive IoT nodes as a stochastic optimization problem. By devising an efficient algorithm based on the branch-and-bound technique, the system can obtain good performance in terms of power consumption and user satisfaction with low complexity. Nevertheless, this algorithm is designed for nonorthogonal multiple access based wireless networks.

In this paper, we are trying to balance the monitoring performance and the whole system energy consumption. An energy-efficient scheduling approach is proposed to decrease the energy cost while maintaining the monitoring performance in an environmental monitoring system. This developed approach is designed for the sensing layer of the monitoring network. The utilized algorithms are relatively simple to operate on chips or low-cost Microprogrammed Control Units (MCUs). The scheduling is based on the approximation of a surrogate model, which is utilized as the reconstruction and analysis tool. Part of the communication operations can be abridged by the prediction of the model. Hence, the system can save energy while maintaining monitoring performance.

The main contributions of this paper are as follows:
1) A decentralized two-tier architecture is designed for environmental monitoring that is appropriate for both outdoor and indoor environments.
2) An energy-efficient scheduling approach is proposed for the monitoring operation. The approach can maintain a high accuracy during monitoring by considering the limited computing capability of LPWA devices.
3) The proposed approach also provides another way for managers to have comprehensive knowledge of the monitoring area.
4) The scheduling approach requires little prior information, thereby decreasing the cost of application.

The remainder of this paper is organized as follows. In Section II, the related work of the environmental monitoring and newly developed LPWAs is introduced. The framework of the environmental monitoring system is described in Section III. Section IV introduces surrogate model-based energy-efficient scheduling. The simulation and tests are performed in Section V. Section VI presents the article’s conclusions and outlines future work.

II. RELATED WORK

The LPWAs and their relative technologies provide many benefits for environmental monitoring. The large communication range, over 10 km, relieves the traditional communication constraints. The star topology decreases the connection and networking costs [8]. Meanwhile, most of the low-cost sensors, the LPWA end-devices, and protocols are
usually designed with low energy consumption to prolong their battery lives and reduce operation cost [18], [19]. Low-cost environmental sensing chips are generally around $1 but with acceptable accuracy for event detection and environmental management. For example, the accuracy of the LM35DZ temperature sensor is approximately 1 degree, whereas the maximum error of the humidity sensor does not exceed 10% [20], [21]. Additionally, unlike past WSNs, the monitoring results from LPWA networks can naturally provide corresponding location information. Furthermore, the wireless end-devices can even work as event detectors due to the development of auto-wakeup technology [22].

Several relative studies have also demonstrated the efficiency of IoT-based environmental monitoring. In [23], Mois et al. proposed an analysis with three IoT-based wireless sensors for environmental monitoring. The research provided an overview of the potential and challenges for application of the three networks and finally demonstrated the efficiency of Bluetooth-based independently networked monitoring systems. In [24], the performance of IoT-based structural health monitoring was discussed. It is highlighted that the voluminous and rapidly generated data caused new problems for managers.

However, testing of LPWA applications has met several problems. For example, the SK Telecom company hosted a Long Range (LoRa) network to track both temperature and humidity. However, this LoRa-based network exposes a large-scale data process problem. Operational cost information cannot be provided for a large network [25]. Additionally, a cyber-physical system for environmental monitoring based on an IoT platform determines the energy defect after testing the battery discharge curves [26].

Meanwhile, the monitored environment also raises other requirements for the monitoring system. First, due to different magnitudes of environmental change and long monitoring intervals, the monitoring system should have high accuracy and strong robustness for adaption to different situations. For example, indoor situations usually have a relatively stable or controllable environment, whereas outdoor environments are universally impenetrable [27]. Second, the results of environment monitoring should be suitable for environmental control. The typical value is not sufficient for regulation in detail. For instance, in heating ventilation air conditioning systems, the extremum values of the monitoring information are highly required to prevent failures and save energy [28].

Furthermore, both the outdoor and indoor environmental monitoring systems have similar problems with wireless communication limitations and geographical differences. The geographical distinction caused environmental differences likewise require distinct monitoring strategies. When outdoor environmental monitoring systems are employed, due to the large scale and complex geographical barriers, wireless communications require relays or base stations to enhance coverage [29]. Meanwhile, the indoor environment has inevitable obstacles that hinder the application of single-layered wireless networks. Hence, access points (APs) or communication relays are required [30].

III. LPWA-BASED MONITORING SYSTEM

As shown in Fig. 1, a hierarchical framework is utilized in the environmental monitoring system. The main idea is to utilize decentralized control tiers to independently help sensors adapt to environmental change. The whole monitoring system is divided into small pieces that can be readily controlled.

The sensing layer is classified into two tiers with star topology. The sensing tier consists of the LPWA-based sensors, such as the LoRa end-devices. The scheduling tier is formed with the scheduling nodes, which consist of the existing AP nodes or wireless communication relays, such as the LoRa gateways or Narrow Band-IoT (NB-IoT) base station. These existing AP nodes and relays provide an appropriate situation for edge computing to pretreat the collected data and make simple decisions. According to energy harvesting methods [5]-[7], these scheduling nodes can easily obtain an adequate energy supply and execute low complexity operations with their MCUs.

Separation of sensing tiers is based on the geographic impediments of the monitoring area. Each sensing subregion can be characterized as one or several barrier-free areas with continuous environmental distribution. Because each subregion has different scheduling nodes, the monitoring strategies can be distinct and targeted. During the operation, the scheduling nodes are designed to make a suitable scheduling for the subsequent operation of the sensing nodes. The monitoring results and the energy consumption information collected from the sensing nodes are the main factors for the next scheduling. At each monitoring step, part of the sensor’s operation may be saved to enhance the energy efficiency of the whole system.

Like other IoT-based systems, the transmission layer is formed with the existing communication networks, such as the cellular network for NB-IoT. The monitoring results are
gathered together in the data or control center to provide a comprehensive view to help managers make better decisions. Because of the requirements of wide deployment and longer operation life, most of the IoT communication technologies are limited by their investment and operation cost. Thus, in this paper, the scheduling design obeys two principles to satisfy the limited computational capabilities of LPWA devices and the scheduling cost during communication.

First, all of the algorithms should have sufficiently simple processes that can be operated on chips or MCUs, even the scheduling analyses in the communication middleware. This principle maintains the low investment cost of the whole monitoring system, which can guarantee wide deployment.

Second, the time and number of communications between the scheduling and sensing nodes should be limited. Though the receiving operation consumes less energy than transmitting, receiving a succession of superfluous commands from the scheduling nodes can still damage the operational life of the sensing nodes.

In this paper, the interactive processes of communications between the scheduling and sensing nodes are illustrated in Fig. 2. The left one is the common point-to-point interactive communication process in the proposed system. The process consists of four steps: the networking step (in purple), the sleeping step (in yellow), the activation step (in black), and the measurement step (in green). Each step can find the corresponding process in the existing LPWA technology, such as the LoRa and NB-IoT in the right. The networking step is intended for system security and networking with mobile nodes. The sleeping step is designed for saving energy during monitoring, and the activation step is used to wake up the sleeping nodes. The proposed scheduling works on the measurement step. By sending measurement requests to the selected sensing nodes, the monitoring system can get sufficient results for a high-accuracy reconstruction. At the same time, the unselected nodes can save energy during data transmission. For end-device-first systems, such as NB-IoT communication in the right, the selection of scheduling responds to the delay or rejects commands to the unselected nodes during the measurement step.

IV. SURROGATE MODEL BASED SCHEDULING
Owing to the complexity and irregular change, it is difficult to describe the environmental distribution with one static model or function. Utilizing a fast data-driven computing model to approximate real results is a promising choice. By approximating the environmental distribution with sparse monitoring results, managers can get a global view of the monitoring area.

In this paper, a surrogate model is used as the estimation algorithm for environmental monitoring. This model is particularly well-suited for multidimension approximation. The surrogate model has been researched and applied in the design and optimization community and has developed many branches, such as polynomial response surfaces and Kriging space mapping. Generally, this model is used to provide approximations of computationally expensive simulations and experiments [31]. For example, the Kriging surrogate model has been utilized in finite element analysis to reduce the computing time for multiobjective robust optimization of electromagnetic devices [32].

In this paper, the Kriging approximation (KA) surrogate model is chosen to describe the monitoring area and estimate the results of abridged nodes. By constructing a KA model based on the collected data, a surrogate model is obtained for the environmental distribution. It is a computer model adapted for high dimensional analysis and expected to significantly reduce the computational burden [31]. With this model, the discrete sensing results from IoT sensors can be converted into a continuous computer model described as

\[
y(x) = f(x)^T \beta + r(\Delta x, \theta)^T \gamma
\]

where \(y(x)\) is the predicted value of the model. \(x\) is the coordinate of the position of the predicted value. \(\Delta x\) is the difference between the positions of the abridged nodes and the operating nodes. \(\beta\) is the parameter of the generalized least squares estimate. \(\theta\) is the correlation function parameter. \(\gamma\) is the correlation factor. All the parameters are estimated by the least squares algorithm, a famous low complexity operation that has operated on chips or MCUs in various applications [33], [34]. \(f(x)\) is the regression model that is a function vector set containing polynomials of orders 0, 1, and 2, for example, \(f(x) = [1, x_1, \ldots, x_n]\). \(r(\Delta x, \theta)\) is the correlation model that can be defined or assumed by the environmental and finite element analysis of the environmental factors, or directly obtained from engineering experience.

In this paper, the KA surrogate model is utilized to decrease the whole system energy consumption while maintaining an acceptable monitoring result. The results of the abridged nodes are predicted from the surrogate model of measured results to save energy. Thus, the energy problem can change to a sampling problem for the modeling. During
the scheduling, fewer sensing results are used to constitute an acceptable KA surrogate model with satisfactory accuracy.

During the scheduling, stratified sampling is used to get representative results from areas with relatively independent environmental characteristics. Generally, environmental monitoring networks are deployed regularly and statically [35]. Hence, each subregion can be divided into several grid subdomains with similar geographic size. The selection of the subdomain size is determined by prior knowledge of the monitoring area, for instance, the deployment of sensors, the influence factor distribution, or the position of the obstacles. The relatively stable areas have fewer and larger subdomains, whereas changeable areas are more separated.

The one-time step of the proposed scheduling is illustrated in Fig. 3. The initial sampling rate of the entire monitoring can be set randomly because it can be quickly adjusted to an adaptive level in the following measurements. At time $t$, the scheduling nodes first send a request to collect monitoring results from the $n_1$ modeling nodes and the $n_2$ checking nodes. Next, a KA surrogate model is built by calculation with the uploaded data from $n_1$ modeling nodes. The results from the checking nodes are utilized to check the accuracy of the newly built model.

The first operation rate of the sensing nodes is
\[ P_{t,1} = \frac{e_{i,t}w_i}{\sum_{i=1}^{n} e_{i,t}w_i} \]  
where $e_{i,t}$ is the remnant energy of node $i$ at time $t$. $n$ is the number of nodes in their subdomain. $w_i$ is the weight of node $i$, which can be calculated as
\[ w_i = 0.5M_{i,t-1} + 0.5 \]
where $M_{i,t-1}$ is the normalized absolute measurement difference of node $i$ in time $t-1$, calculated as
\[ M_{i,t-1} = \frac{|m_{i,t-1} - m_{i-1}|}{m_{\text{max},t-1} - m_{i-1}} \]
where $m_{i,t-1}$ is the measurement result of node $i$ at time $t-1$. $m_{\text{max},t-1}$ is the mean value of measurement results in that subdomain. $m_{\text{max},t-1}$ is the maximum measurement result in that subdomain at time $t-1$. The setting of weight helps the scheduling node have higher possibility to get the extrema in the next monitoring. When the past results have similar values, the remnant battery energy will be the determining factor.

The $n_2$ checking nodes are selected by the probability $P'_{i,t}$, where $n_2 = 25\% \times n_1$. The results are compared with the predicted results from the formed KA surrogate model to check the accuracy. The probability of the checking node selection is based on their remnant energy. $P'_{i,t}$ can be calculated as
\[ P'_{i,t} = \frac{E_{i,t}}{E_{t}} \]
where $E_{i}$ is the sum of the remnant energy of the rest of the nodes. This probability definition is utilized to balance the energy consumption of the whole system while obtaining more uncertain information. In the checking operation, the maximum tolerable error is set by the requirements of the monitoring system.

Unless the monitoring results have sufficiently high accuracy, the scheduling node will resend the requests to obtain new measurements. The results from the $n_3$ reselected
modeling nodes are used to build a new KA surrogate model together with the measured results. $n_3$ can be calculated as

$$n_3 = 20\% \left( N - n_1 - n_2 \right)$$

where $N$ is the number of sensing nodes in this subregion. The newly obtained information from checking nodes is used to check the accuracy of the new model.

By the multiple-times of the measurements and communications, the appropriate results representing the environmental distribution at time $t$, will be finally collected. Next, after uploading the monitoring results, the scheduling node will calculate parameters for the next monitoring. 50% of the collected monitoring results are utilized to rebuild a KA surrogate model. 25% of the remaining results are utilized to check their accuracy. If the accuracy can achieve our setting goal, the sampling rate at time $t+1$ will decrease to a sublevel of the settings.

With the self-adaptive operation rate, the sensing node operation, as well as the number of resending requests, can be adapted to environmental change. The large mutations, usually from a stable state to a changeable state, will be adapted in one time operation with several resending operations, and the stabilizing change will be solved in the following monitoring. Hence, the energy efficiency of our proposed approach can be maintained at a low level and even meet environmental mutations.

V. SIMULATIONS AND TESTS

The simulation and tests of our proposed scheduling method are based on a time-varying environmental field simulation calculated by COMSOL Multiphysics. We choose temperature to represent the monitoring objects because most environmental monitoring objects, such as temperature, humidity, and air quality, have a continuous distribution with analogous characteristics that can be easily disturbed by air flow.

In the temperature field simulation, we construct a 160×160 m² barrier-free area as one subregion to simulate the temperature variation. The whole area is averagely divided into 16 subdomains during the tests. Three sides of the area are defined as open boundaries, and the other is set as a wall. The initial setting of the simulation is configured as an isothermal field at 10 degrees Celsius. Two inlets are defined at the two sides of the boundaries to simulate the outside influence, and one recovery inlet is set to recover the temperature. In the stable state, three inlets provide flows with little difference to simulate the slow fluctuation of the temperature field. In the other states, the temperature difference is distributed from 3 to over 10 degrees Celsius. The wind speed is randomly set approximately 0.5 m/s (calm wind) during the stable state and is increased to 5–10 m/s (strong wind) when simulating the uncertainty of temperature. A uniformly distributed noise is added to the finite element simulation results to act as measurement error. During all the tests, the Gaussian function is utilized as the correlation function. Second order polynomials are used as the regression model of the KA surrogate model.

In the simulation of energy efficiency, the RNDU470T LoRa terminal and LMT70 temperature sensor are chosen as the main energy consumption chips. The electrical parameters are utilized as the simulation parameters. When the sensing node is linked to a LoRa gateway (the scheduling node), with 3.3 V typical supply voltage, the current drain in the receiving mode is 13 mA, and in sending mode it is 88 mA. When the node operates in sleeping mode, the energy consumption of transmission chips is 1.4 µA. For each measurement, the sensor requires a 9.2 µA typical power supply current and 1 ms power-on time. Additionally, it is assumed that there will be no collisions during the communication. The receiving time is 100 ms. The sending time is 200 ms.

One reconstruction result with the KA surrogate model is shown in Fig. 4. The results are calculated with 5 degrees Celsius temperature difference and 0.3 degrees measurement accuracy. The black arrows are the inflow directions which cause the temperature difference. The black points are the averagely deployed sensors which are utilized to calculate the model. When utilizing 25% of the sensors to detect and model the temperature distribution, the mean square error (MSE) of the predicted results is 0.94. The mean absolute error (MAE) is 0.50. The results in Fig. 4 have directly indicated a reconstructed view for the temperature distribution. Hence, the KA surrogate model is demonstrated to be a potential reference for environmental control and management.

To testify to the performance of the proposed scheduling approach, the time-varying temperature field simulation results are monitored 200 times. The maximum value of the tolerable error is set to 1. The average tolerable error is set to 0.7, which is a common error for low-cost sensors. The initial sampling rate is set to 80%. The scheduling node collects information from all the sensing nodes at the initial operation. The temperature field simulation is started from the stable state. After monitoring 60 times, inlet 1 starts
importing 15°C air flow. At the 90th operation, inlet 2 begins to import 20°C flows. The 120th operation starts the recovery inlet to subside the temperature change.

The results in Figs. 5 to 8 show that the proposed scheduling approach has high energy efficiency with acceptable monitoring performance. Fig. 5 shows the node operating rates in these different states. The average true value of the temperature can partly represent the temperature change during the simulation. When the temperature changes quickly, the rate is raised to a high level to get better monitoring results. The black letters represent the different temperature varying phases. Section A represents the stable state, where the temperature is distributed averagely and changes little. Sections B and C, respectively, represent small and large fluctuations in temperature distribution, where the flows from the inlets are launched to influence the temperature. Section D is a transitory state where the distribution changes quickly and requires high monitoring. Section E is a dynamic state where the temperature distribution stabilizes gradually.

A comparison between the operation and state change proves the adaptation of the proposed scheduling approach for different environments. At the beginning of the simulation, the initial operation rate is set much higher than the system requires. The rate decreases after several operations, and quickly achieves better energy efficiency. In contrast, when the state becomes unordered, similar to the boundary between Sections A and B, the operation rate is promptly increased to a higher level. Because of the round down calculation during subdomain sampling, the operation rate is relatively smaller than the designed sampling rate.

Fig. 6 provides the MSE change, and the MAE of the predicted results of the abridged nodes. The sensing error represents the measurement errors when the abridged nodes are taken into operations. Combined with Fig. 5, although the fluctuations of the MSE and the MAE become more violent in the dynamic state, the values are still maintained at a sufficiently low level that even the temperature changes quickly. This test proves the monitoring performance of the proposed approach that has a strong robustness in different environmental states. With the application of our scheduling approach, the errors of the abridged nodes increase a little at a low level.

Fig. 7 shows the energy consumption of the LoRa network communication in 200 simulations. The variance of all of the sensing results is utilized to describe the dispersion degree of the temperature distribution. The consumption is started with a 200 mAh battery, which is assumed as the power source of the sensor node during our simulation. In this simulation, the energy consumption rate changes in different states, and mainly increases with the variance. In this simulation, the energy consumption of the whole system decreased 41.99%. The node with minimum final energy, which is the main factor of the whole system operation life, saved 35.74% less energy.
Fig. 8 provides the request times from the scheduling node during the simulation. The first sampling rates are shown in the right coordinate axis. Mostly, the scheduling node only sends one request for enough monitoring results. Only the conditions with the small and changeable fluctuations, such as section B and the forepart of section E, need multiple requests. The results indicate that though the first sampling cannot achieve the expected monitoring quality, the energy consumption of the whole monitoring is still sufficiently low.

![FIGURE 9. Operation life of LoRa-based monitoring network in long-term simulation.](image)

A long-term simulation is conducted for the operation of a LoRa-based monitoring network. We define the operation life of the network as the life of the node that first ran out of its battery energy. The tendency of communication energy consumption in different states is analogous to the curves in Fig. 7. It is assumed that each node is powered by a 200 mAh battery, and the LoRa gateway, which is the scheduling node, sends monitoring requests every 5 minutes. The results are shown in Fig. 9. This figure indicates that the proposed scheduling method can prolong the monitoring system operation life up to 136.22%.

Evaluation of the operation life with different length of uploaded data is proposed in Table I. The transmission time is calculated by the LoRa Calculator from Semtech [36]. The central frequency is 865 kHz. The spreading factor is 12. The bandwidth is 500 kHz. The coding rate is 4/5. The total preamble length is 12.25 symbols. It is shown that the proposed scheduling can provide better energy efficiency with larger data sets.

<table>
<thead>
<tr>
<th>Table I. Operation lives in a dynamic state</th>
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<tbody>
<tr>
<td>Data size /Bytes</td>
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<tr>
<td>Transmit time /ms</td>
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<tr>
<td>Operation life without scheduling /day</td>
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<tr>
<td>Increase ratio of operation life /%</td>
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VI. CONCLUSIONS

In this paper, an LPWA-based monitoring system is proposed for environmental monitoring. This system has a decentralized framework that owns the scheduling nodes to schedule the operation of the sensing nodes. The proposed scheduling approach is based on the approximation of the KA surrogate model that aims to save energy while maintaining high monitoring performance. The scheduling approach is designed for the current LPWA devices, which have low computational capability. The simulation results validate the energy efficiency and monitoring performance of our proposed approach. Future work will concentrate on improvement of the approximate models in different environments.

REFERENCES


