Monitoring Passive Wireless Devices

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Research Article

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Abstract—This study suggests using a user-initiated detecting and data gathering from power-limited and even passive wireless devices, such as passive RFID tags, wireless sensor networks (WSNs), and Internet of Things (IoT) devices, that either power limitation or poor cellular coverage prevents them from communicating directly with wireless networks. While previous studies focused on sensors that continuously transmit their data, the focus of this study is on passive devices. The key idea is that instead of receiving the data transmitted by the sensor nodes, an external device (a reader), such as an unnamed aerial vehicle (UAV), or a smartphone is used to detect IoT devices and read the data stored in the sensor nodes, and then to deliver it to the cloud, in which it is stored and processed. While previous studies on UAV-aided data collection from WSNs focused on the UAV path planning, the focus of this study is on the rate at which the passive sensor nodes should be polled. That is, to find the minimal monitoring rate that still guarantees accurate and reliable data collection.

The proposed scheme enables us to deploy wireless sensor networks over a large geographic area (e.g., for agricultural applications), in which the cellular coverage is very poor if any. Furthermore, the usage of initiated data collection can enable the deployment of passive WSNs. Thus, can significantly reduce both the operational cost, as well as the deployment cost, of the WSN.

Keywords: passive wireless sensor networks, monitoring low power devices, data collection.

I. INTRODUCTION

The number of Internet of Things (IoT) devices is rapidly growing. Power-limited IoT devices suffer from severe constraints on their battery consumption, processing, and memory capabilities. Passive Radio Frequency Identification (RFID) tags are used to mark animals in farms, and items in warehouses, retail stores, and along assembly lines installed in factories. Wireless sensor networks consist of sensors, processors, and radio frequencies (RF) modules. A crucial factor for realizing a sustainable battery-powered IoT device or WSN is battery maintenance. Several approaches have been proposed to overcome battery limitations. These approaches include IoT-dedicated infrastructure, energy-efficient protocols, energy harvesting, and efficient data gathering techniques. Unfortunately, due to price and power consumption limitations, these approaches are inadequate for WSNs deployed over a large geographic area. For instance, for agricultural applications.

This study suggests to use a dedicated device, referred to as a "reader", aiming to reduce, and under certain conditions, even to eliminate, the power consumption of the IoT devices and sensor nodes in WSNs. The reader collects the data from the sensor nodes and transmits it to the network. The reader acts similarly to a mobile sink, with one major difference:

the sensor nodes do not have to transmit their data to the reader, which is capable to read this data from the sensors. That means that theocratically, this approach can support even battery-less sensor nodes. For this extreme scenario, the power consumption of the sensor nodes in the WSN is zero.

A. Background and related work

Energy efficiency has been recognized as a major issue for realizing IoT devices and WSNs. Specifically, battery maintenance has become a limiting factor for deploying a WSN over a large-scale area. Reducing the battery consumption of sensor nodes in WSNs is crucial to overcome battery limitations.

Many studies have addressed the issue of reducing battery consumption in WSNs. The most common approach is to use energy-saving protocols, such as Narrowband-IoT (NB-IoT) [11], ZigBee, and Bluetooth low energy (BLE). However, due to their short range, the implementation of these protocols for WSNs deployed over a large scale area are very expensive. Since multi-hop transmission must be used, we get a shorter lifetime of the sensor node batteries, especially for those sensor nodes that are close to the sink.

The commercial solution for low-power IoT devices is to deploy a new IoT-dedicated infrastructure, such as LPWAN [9]. Examples for commercial solutions based on a dedicated infrastructure are $SigFox$ [16] and $FitBit$ [2]. Unfortunately, due to its short range, this solution is very expensive. Moreover, it is not applicable for poor coverage areas. Therefore, this solution is not applicable neither for rural areas, nor for WSNs deployed over a large scale geographic area.

Another approach for reducing battery power consumption is energy harvesting. See, for instance in [22], in which a solar-based energy harvesting was used for WSNs. The usage of energy harvesting techniques enables to extend the lifetime of the sensor nodes. However, this extension is achieved at the expense of increasing the cost of the sensor nodes. Since the number of sensor nodes installed in a typical WSN deployed over a large geographic area is expected to be very high, we seek to reduce their cost.

The issue of a UAV-assisted data collection from WSNs has been addressed by several studies [1], [6], [4], [7], [8], [12], [13], [19], [21]. The usage of a mobile sink for data collection in WSNs was addressed in [5], [8], [19]. However, in these studies, the sensor nodes still have to transmit as usual, and the problem discussed is the construction of the shortest path that covers all the sensor nodes. The main concern of the studies mentioned above is the data collection path planning. Our concern is on the monitoring rate at which the data

should be collected from the sensor nodes. To the best of our knowledge, this issue was not previously addressed. This paper is an extended version of the study presented in Wireless Telecommunication Symposium (WTS) 2021 conference [10].

B. Contributions of this work

The focus of this study is on the optimal monitoring rate, at which the data collection process should be initiated. Commercial solutions for data collecting from IoT devices, such as $SigFox$ [16] and $FitBit$ [2], rely on a dedicated infrastructure, such that the sensor nodes are expected to transmit their data to a nearby access point, which must be very close, within 15 feet of the sensor nodes. While previous studies considered WSNs in which the sensor nodes continuously transmit data that should be collected by a sink node (either static or mobile), the key idea of this study is to use a dedicated device, such as a smartphone, or a UAV, referred to as a "mobile reader". While previous studies concerning a UAV-assisted data collection from WSNs focused on the UAV path planning, assuming that the sensor nodes continuously transmit their data, our concern is on the monitoring rate of the sensor nodes, which either power limitation or poor cellular coverage prevents them for transmitting. The mobile reader initiates a data collection process, during which it actively collects (reads) the data from the sensor nodes, which do not have to transmit data at all.

This method is especially suitable for WSNs deployed over a large scale geographic area. For instance, for agricultural applications, such as monitoring cattle and sheep farms, or for large plantation farms. For these applications, there is a need for WSNs to be deployed over a large geographic area. For cattle and sheep farms, the sensor nodes should be mobile. Even an RFID tag can be used to track an animal. These farms are typically located in areas that suffer from a lack of cellular coverage. Due to their relatively large geographic area, they are not suitable for networks and protocols based on short-distance communication. For these reasons, traditional WSNs do not apply to them.

C. Paper organization

The rest of this paper is organized as follows: Model and problem formulation are given in Section II. The data collection scheme is introduced and analyzed in Section III. Performance analysis and simulation results are described in Section IV. Finally, summary and concluding remarks are provided in Section V.

II. MODEL AND PROBLEM FORMULATION

We consider a system consists of three elements: a power-limited IoT device, to be referred to as a sensor node (SN), a mobile reader (MR), which is used as a mobile sink that can move seamlessly across the network, and a processing unit (PU) that receives the data collected by the MR. The goal of the PU is to store and process the data collected from the sensor nodes, and evaluate the desired rate of data sampling, based on history. The goal of the MR is to enable network connectivity to the SNs, even in areas which suffer from poor cellular coverage. The MR can be, preferably, a UAV equipped with a dedicated reader device (e.g., an RFID reader), or even a smartphone leveraged to detect IoT devices. Many smartphone producers leverage their smartphones to detect IoT devices. For instance, in [20] this feature was used for IoT device authentication. The usage of smartphones for reading the data stored in IoT devices is already available commercially. See, for instance, $FitBit$ [2]. The SN can be either static or mobile. It can be, for instance, either a sensor (e.g., for measuring temperature, humidity, pressure, etc.), or an RFID tag (e.g., for tracking animals), or a wearable IoT device. Very often, the SN has a very limited power capacity, or it can be even a battery-less device (e.g., passive RFID tags). Thus, the model assumption is that the SN electric power capacity is very limited if any. The SN has severe constraints on its memory capacity and processing power. The SN is assumed to store a piece of information which can be either transmitted by the SN (in case it is capable to transmit), or retrieved by a special device called "reader" (i.e., the MR). In general, the SN does not have to possess an IP address. It is assumed that time is slotted. Since the issue of UAV path planning has been extensively discussed by previous studies (see, for instance, in [1], [6], [4], [7], [8], [12], [13], [19], [21]), the focus of this study is only on the monitoring rate of the IoT device, or the WSN, which consists of sensor nodes (SNs), and a mobile reader (MR).

III. THE DATA COLLECTION SCHEME

The key idea of our scheme is to use a dedicated device, for instance, a smartphone, or a UAV, referred to as MR, for accessing the data stored in the SNs. While traditionally each SN transmits its data either to the nearest sink node or to its nearest neighbors (using multi-hop transmission), we consider passive devices. Based on run-time knowledge processed in the cloud, the MR initiates a data collection procedure, during which it reads the data stored in the SNs. The MR either access the data stored in the IoT devices carried by the same person who owns the MR (e.g., a smartphone can read the data stored in healthcare devices), or travels through the WSN. The MR delivers this data to the nearest base station (BS), to be eventually stored and processed in the cloud. That means that the memory size of the MR should be sufficient to store the collected data until it is transmitted to the nearest BS. The main focus of this study is the evaluation of the optimal rate at which the MR should monitor the SNs.

The MR which is used as a mobile sink, uses a short-range communication to its SNs. The MR-SN connection is established by a proximity-based authentication process, as described in detail in [20]. Therefore, when applied for WSNs, the UAV flight altitude should be very low (2-10 meters). The MR is also used as the SNs gateway to the wireless network. Since the MR-SNs link is based on a short-range communication, it is more protected against hostile attacks [20].

A. Analysis

The data collected by the MR is delivered to the cloud, which adjusts the rate at which the WSN data is collected and then disseminated across the network, to run-time knowledge. Consequently, the amount of data produced by the WSN and disseminated across the network, as well as the power consumed by the WSN, are both reduced. The implementation of this task is not feasible for most SNs, since it usually uses highly computational algorithms based on approximation techniques and run-time knowledge. For this reason, previous studies addressing this issue proposed network-based solutions, in which this task is performed by a network element. Some of these studies are described in [18].

The key idea of this study is the usage of *initiated* data collection, activated at discrete time points. Our main concern is *when* to initiate the next data collection process. Therefore, our monitoring model is based on a discrete time Markovian model. During each time slot, an SN can be at any one of N states, denoted by i, $i = 1...N$. For instance, a set of values (e.g., pressure, temperature) within a pre-specified range can be considered as a "state". The states can be classified as "normal", or as such that require special attention. For sensors (e.g., RFID tags) used for tracking animals, a "state" can be the area unit in which the animal is located. The time is slotted, and at each time slot, an animal can move from one zone ("a state") to another. A state transition matrix S, whose dimension is $N \times N$, is associated for each SN. The element s_{ij} in S is the SN state transition probability from state i to state j during one time slot. For instance, moving from area i to area j (for an SN used to track an animal), or when the temperature measured by the SN is changed by one unit. Using the SN history, S can be constructed by the cloud. We assume that during one time slot the SN can make at most one transition from one state to another. It is further assumed that the state transition matrix S is ergodic and regular, implying that $\det(S) \neq 0$. The probability for state transition from state i to state j during t time slots is denoted by s_{ij}^t. That is, $s_{ij}^t = Pr[M(t' + t) = j \mid M(t') = i]$; where the SN state at time t is denoted by $M(t)$, $s_{ij}^0 = 1$ if $i = j$ and 0 if $i \neq j$. The usage of Markovian model implies that s_{ij}^t does not depend on t'. Denoting the probability to find the SN in state k at time t by $\phi_k(t)$, $t = 0, 1, 2...$, and let $\phi(t) = (\phi_1(t), \ldots, \phi_N(t))$. We denote the limiting state probability of the SN in steady state, $\phi(\infty)$, by ϕ. The state probability of the SN $\phi(t)$ is given by: $\phi(t) = \phi(0)S^t$.

Our goal is to obtain the desired rate of monitoring an SN. That is, we seek to find the maximal time interval during which the data stored in the SN does not change significantly, therefore there is no need to collect this data.

Let x be the last known state of an SN d, at time $t = 0$. In order to optimize the rate of monitoring d, our interest is to obtain the probability that d will stay in its state at any given time t. Given that at time $t = 0$ d was in state x, then the probability to find d in this state at time t is given by:

$$\phi_x(t) = r_x S^t r_x'. \tag{1}$$

Where r_x is the row vector whose xth element is 1, and all the other elements are zero, and r_x' is the column vector that is the transpose of r_x. Since the number of states N can be very large, the size of the state transition matrix S may be very large. Therefore an exact solution of Equation 1 has a relatively high computational complexity. Thus, our goal is to find an approximation solution for the transitivity of d over time. We use the *Shrinkage Factor* defined in [3], to get that:

$$|\phi_i(\infty) - \phi_i(t)| \approx G|\det(S)|^{\frac{t}{N-1}}, \tag{2}$$

where G is a constant to be determined. Requiring that $\phi(\infty)$ and $\phi_i(0)$, as determined by Equation 2, are exact, and denoting $\phi(\infty)$ and $\phi_i(\infty)$ by ϕ and ϕ_i, respectively, we get that:

$$\phi_i(t) \approx \phi_i + [\phi_i(0) - \phi_i]|\det(S)|^{t/(N-1)}, \tag{3}$$

We define α by:

$$\alpha = |\det(S)|^{1/(N-1)}. \tag{4}$$

The parameter $\alpha^{-(N-1)}$ describes the rate at which the Markov chain converges to its steady state. Therefore, we identify α ($0 < \alpha < 1$) as the tendency of the SN to remain in its current state. Whenever the parameter α approaches 1, the state transition matrix S approaches the unity matrix, and the state of the SN remains almost the same over time. Whenever α approaches 0, the SN converges to its steady state instantaneously, independently of its initial state. Hence, the SN transitivity is maximized.

Equation 3 determines an approximation for the distance between $\phi_i(t)$ and ϕ_i. An upper bound on this approximation was proposed in [15]. Denoting the second largest eigenvalue of the state transition matrix S by Γ_{sec}, an upper bound on the distance between $\phi_i(t)$ and ϕ_i is given by:

$$|\phi_i(t) - \phi_i| \leq \frac{\phi_i}{\phi_{min}} \Gamma_{sec}{}^t , \tag{5}$$

where ϕ_{min} is the smallest component of ϕ: $\phi_{min} = min\{\phi_i : 1 \leq i \leq N\}$. It was shown in [14] that since S is ergodic, $|\Gamma_{sec}| < 1$. Denoting the approximated value of $\phi_i(t)$ given in Equation 3 by $\phi_i'(t)$ we get that:

$$|\phi_i'(t) - \phi_i| = |\phi_i(0) - \phi_i|\alpha^t. \tag{6}$$

Our interest is in the distance between the approximated and real value of $\phi_i(t)$. Denoting this difference by $\epsilon(t)$, and using the triangle inequality, it follows from Equation 5 and Equation 6 that:

$$\epsilon(t) = |\phi_i'(t) - \phi_i(t)| \leq \frac{\phi_i}{\phi_{min}} \Gamma_{sec}{}^t + |\phi_i'(t) - \phi_i| \tag{7}$$

Substitute Equations 5, 6 in Equation 7 we get that:

$$\epsilon(t) \leq \begin{cases} \frac{\phi_i}{\phi_{min}} \Gamma_{sec}{}^t + \phi_i \alpha^t & \text{if } \phi_i \geq 1/2 \\ \frac{\phi_i}{\phi_{min}} \Gamma_{sec}{}^t + (1 - \phi_i)\alpha^t & \text{if } \phi_i < 1/2 \end{cases} \tag{8}$$

It follows from the above analysis that as long as ϕ_{min} is not extremely small relative to other ϕ_i's, and Γ_{sec} is bounded away from 1, the upper bound on the approximation error

suggested in Equation 3 can be neglected. Both conditions hold for a broad class of Markov chains, which can be used for realistic sensor modeling, and are rarely violated in practice.

The upper bound on the approximation error determined in Equation 8 can be used for controlling the monitoring rate of the WSN. Given the desired accuracy level Δ for an SN d, we can use the upper bound on the approximation error given in Equation 8 to obtain the monitoring rate for d. The length T of the time interval between two consecutive data collection actions from d is determined by the condition:

$$\epsilon(T) \geq \Delta. \tag{9}$$

Where the upper bound on $\epsilon(T)$ is determined by Equation 8. Equation 9 determines the desired rate $\frac{1}{T}$ of monitoring the WSN. It follows from Equation 8 that the approximation error decreases exponentially with time. Therefore, as time increases we can approximate the SN state accurately using Equation 3. Clearly, the monitoring rate should be state-depended. For instance, the state transition matrix S may depend on the time-in-day, season, etc... The information obtained by the WSN can be processed in the cloud and used to determine the next time of data collection.

It follows from Equation 8 that the approximation error $\epsilon(t)$ decreases exponentially with time. The reason for this observation is that $\epsilon(t)$ depends on α^t. It follows from Equation 4 that the parameter α depends on the determinant of S, that all its elements are probabilities, i.e. non-negative numbers between 0 and 1. Therefore, α^t decreases exponentially with t. The same reasoning applies for $\Gamma_{sec}{}^t$, since $0 < \Gamma_{sec} < 1$. Therefore, it follows from Equation 8 that the approximation error $\epsilon(t)$ decreases exponentially with time.

It follows from Equation 3 and Equation 8 that α reflects the rate of the WSN information aging. The factor α^t which appears in both equations reflects the value of prior knowledge obtained at time $t = 0$. The future value of the information obtained during the data collection process depends on α. As α approaches 1, the SN is more stable, and it is likely to remain in its current state for a relatively long time. On the other hand, as α approaches zero, the future value of the information obtained during the data collection process decreases very rapidly, and there is a need for frequent data collection processes.

Upon data collection from an SN d, to be found in state x, the benefit of reading the data stored in d decreases with the steady state probability ϕ_x to find d in its current state x. That is, the benefit is given by $1 - \phi_x$. The reason for this behavior is that the benefit of reading the data stored in d increases with the "surprise", which is the difference between the value expected to be found, which depends on the steady state probability vector ϕ, and the probability to find d in state x, which is the real value of d at the time of data collection. As the state x of d is unlikely - that is as ϕ_x approaches zero, the "surprise" is greater, and therefore the benefit is greater.

The analysis above holds for a single SN. In a real WSN, we should have a large number of SNs. Thus, the probabilistic approach described above should be accurate when applied on a real WSN which consists of many SNs.

Given that at time $t = 0$, an SN d is in state x (i.e., the value of the data stored in d is within a specific range x), the probability that d will remain in its current state x during the next t time units is given by:

$$S_{xx}^t = (1 - \sum_{j \neq x} S_{xj})^t. \tag{10}$$

Thus, it follows from Equation 10 that, after obtaining the data (i.e., the state) x stored in an SN d at time $t = 0$, the confidence in this value decreases exponentially with time, and depends on the state transition probability S_{xx}. This confidence level can be used to determine an upper bound on the rate of monitoring the SN d.

The discrete time Markovian model used in this section for the analysis of the data stored in the SNs can be used for other applications of WSNs. For instance, the states of the SN can describe the SN location. This usage is applicable, for instance, for monitoring cattle and sheep farms. For these applications, each animal can be marked with an RFID tag that enables to track the animal location. The area covered by the WSN is partitioned into zones. A state i indicates that the animal is currently residing in the zone i. The state transition matrix S for this application describes the movement probability from one zone (the "state") to another zone. A UAV equipped with an RFID reader can be used to track the animals. Another possible application for this usage of the model described above is for monitoring a large geographic area covered with many surveillance cameras. Using UAV - SNs communication we can track objects moving across the WSN.

IV. PERFORMANCE ANALYSIS AND SIMULATION RESULTS

The proposed scheme enables to reduce both the deployment cost, as well as the operational cost of WSNs. These goals are achieved by reducing the cost of the SNs, that do not have to use expensive batteries for frequent data transmissions and extending their lifetime. Since sensors acquisition and battery maintenance cost are the most significant cost factors that affect the deployment and operational cost of the WSN, reducing their cost can significantly reduce the cost of WSNs. Moreover, there is no need for RF modules, processors, and sink nodes, which can be replaced by either a smartphone or a single UAV traveling across the WSN.

The efficiency of the data collection process can be further increased by limiting the data collection process to the specific areas that require special attention, in response to reported events (e.g., by using a UAV-installed camera). There is no need to scan every SN in the WSN.

Alternatively, the mobile reader can be used by a "conventional" WSN, in which the SNs can transmit. In this scenario, each time a group of SNs transmits exceptional data (e.g., for forest monitoring) a UAV can be sent for detailed monitoring on the suspected area. Both goals, cost reduction, and real time detailed monitoring can be achieved simultaneously. For instance, by using two types of SNs within the same WSN -

a relatively small number of more expensive SNs, which can transmit data, and a large number of cheaper SNs - which do not transmit data, but should be monitored under certain conditions. The UAV can collect data from the WSN, and transmits it to a BS located far away from the sensing area. Consequently, the multi-hop transmission between the SNs can be avoided, and the area covered by the WSN can be extended.

A. Simulation results

In this section numerical experiments were used for evaluating the performance of the proposed data gathering method.

The system under consideration is a collection of greenhouses, monitored by 10000 SNs arranged in a rectangle shape, of sizes 10 km X 10 km. The SNs are placed in 100 lines, with a distance of 100 meters between two neighboring lines, and a distance of 100 meters between two neighboring SNs in the same line. For this system, the MR can be even a smartphone equipped with an RFID reader [20]. Each SN monitors the temperature, humidity, CO_2 concentration, and light within its greenhouse and can be found in any of 20 states. The combination of these parameters defines the SN state. The treatment required for the plant is determined by the state of the local SN, for instance: "ready for plantation", "needs more water", "ready for picking", etc. The state transition matrix is constructed in the cloud, based on history. Since the data stored in each SN is unique for the greenhouse in which this SN is located, data sampling methods are not feasible. The performance metric considered is the quality of the proposed approximation method and the rate of data collections/transmissions per time unit.

The quality of the approximation method suggested in Equation 3 is considered in Figure 1. 10 20x20 matrices were considered, reflecting 10 types of the state transition matrix S. The real value of each component of the vector $\phi(t)$ was compared with the approximated value of the same component. Figure 1 depicts the arithmetic average of the approximation error over all the experiments, as a function of time. It is clearly demonstrated that the difference between the real and approximated values are negligible, and decreases exponentially with time, as predicted in Section III.

Figure 2 depicts the average number of data collections per SN, for passive WSN (PWSN), versus traditional (transmitting) WSN (TWSN), in which all the SNs must transmit. The TWSN is partitioned into clusters. Each SN transmits its data to its cluster head whenever its state is changed. The cluster heads use multi-hop transmission between them to deliver the data to the nearest BS. Two types of TWSN are considered - with no multi-hop transmission (i.e., it consists of one cluster), and with three hops transmission per SN (i.e., each cluster head uses on average two transmissions to another cluster head, which delivers the information to the nearest BS). It is further assumed that the energy required for reading the information from each SN is considered equal to that required for one data transmission in the TWSN under consideration. The number of data transmissions/collections is depicted as a function of time (measured in time units).
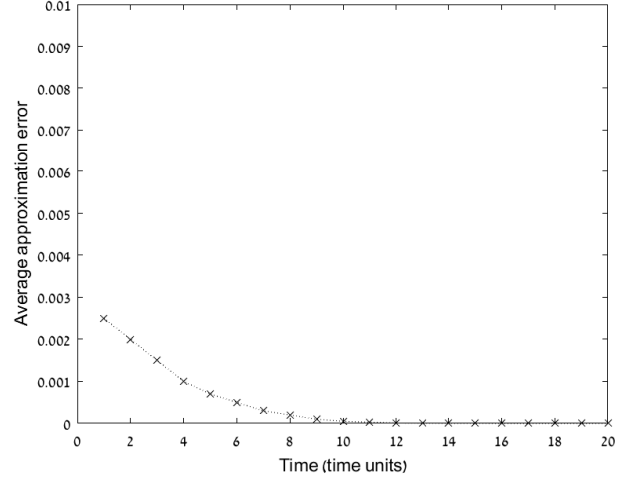

Fig. 1: The quality of approximation, expressed by the average approximation error, as a function of time (in time units).

The TWSN is distinguished from the PWSN. The PWSN uses a smartphone/UAV for data collection whenever the time duration T since the last data collection is sufficiently large, such that a state transition is expected. For the TWSN with no multi-hop transmission, each SN transmits to the nearest sink. Thus, each data transmission must be followed by another transmission - of the sink. For the TWSN with three hops transmission, the average number of data transmissions per SN is 4 transmissions - one to a neighbor of the SN (its cluster head), an average of two messages transmitted between the cluster heads, and a fourth transmission - to deliver the information to the nearest BS. Consequently, even though the average number of data collections per SN for the PWSN is significantly larger than the equivalent number transmitted by an SN in the TWSN which stores the data, the average number of data transmissions generated by the TWSN is larger than the equivalent number generated by the PWSN.

The scenarios depicted in Figure 2 are the worst cases for a PWSN. In reality, even if a TWSN deployed over a large area has cellular coverage, due to its large area a typical SN should need several multi-hop transmissions until the data is delivered to the nearest BS. Therefore, in reality, the power consumed by a TWSN should be significantly higher than the equivalent power consumed by a PWSN. Note that the average number of data collection events from an SN for the PWSN in the simulation was significantly higher than the average number of data transmissions generated by the same SN in the TWSN (before taking into consideration multi-hop transmissions until the data is delivered to the nearest BS). The reason for this is that, in the scenarios described in Figure 2, the SNs in the TWSN transmit the minimum number of messages. An SN should transmit data only whenever the detected value differs from its last detected value. On the other hand, using the suggested approximation method, data collection is performed

whenever a state transition is expected. As it is shown in Figure 1, the average value of the approximation error is significantly smaller than the upper bound on the approximation accuracy obtained in Equation 3. Therefore, the rate of data collection events must be higher than the optimal (i.e., the minimal) number of data transmissions required for keeping the approximation error below its upper bound. However, since a TWSN must rely on multi-hop transmissions, the total power it consumes is still higher than the power consumed by a PWSN, as depicted in Figure 2. It should be noted that the cluster heads in TWSN transmit more messages than the other SNs, implying higher maintenance costs.
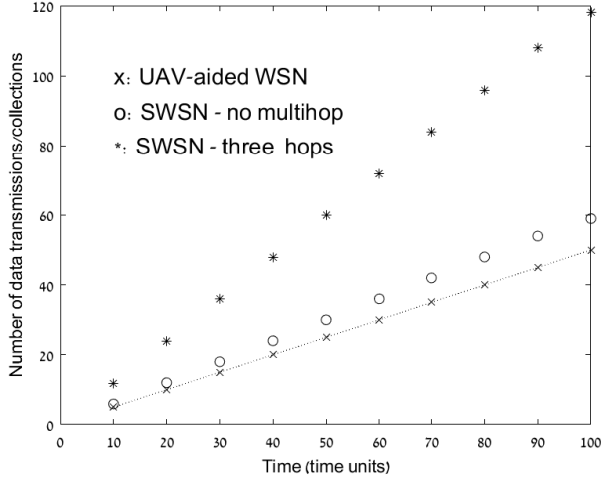

Fig. 2: The average number of data transmissions/collections per SN, for a PWSN, versus transmitting WSN (TWSN) with no multi-hop transmission, and with three hops transmission per SN, as a function of time (measured in time units).

Figure 2 demonstrates that the power consumed by the PWSN is less than the equivalent power consumed by the TWSN, while the data collection rate of the PWSN is higher than the equivalent rate of the TWSN. Thus, we get better monitoring (i.e., higher data collection rate) for less price.

Figure 3 examines the power consumed by a PWSN versus the power consumed by a TWSN, for the same data collection rate. That is, the same WSNs used for Figure 2 transmit/collect data every T time units, where T is a constant. This is a realistic scenario, expected from a real WSN. The value used in Figure 3 is $T = 10$ time units. Figure 3 demonstrates that for the same data collection rate, the power consumed by the PWSN is significantly less than the equivalent cost consumed by the TWSN, since the multi-hop transmission between cluster heads is completely avoided for the PWSN. The power-saving increases linearly with the average number of multi-hop transmissions. Therefore, the superiority of PWSN over TWSN increases linearly with its size.
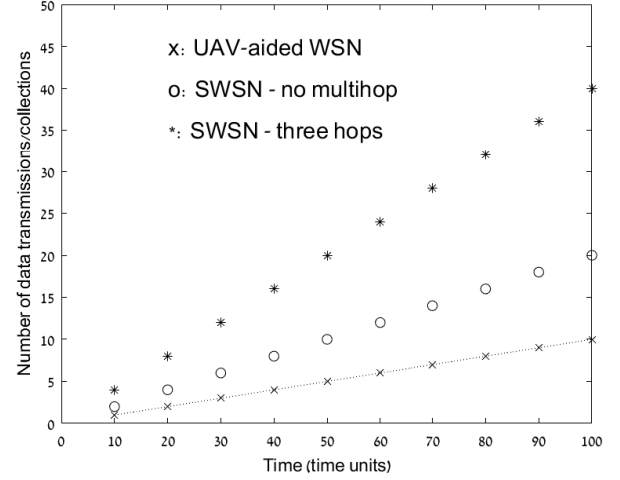

Fig. 3: The average number of data transmissions/collections per SN, for a PWSN, versus TWSN, for the same data collection rate, as a function of time (measured in time units).

V. Summary and Concluding Remarks

It was shown that the usage of initiated data collection from a WSN enables WSNs deployment in areas that are poorly covered by cellular networks. Moreover, it can potentially reduce, and under certain conditions even eliminate, the number of data transmissions generated by the SNs. Consequently, the SNs do not need a multi-hop transmission and can use cheaper batteries. Since battery maintenance and sensor acquisition cost are the major cost factors affecting the cost of a WSN, both the WSN deployment cost as well as the operational cost should be reduced.

VI. Declarations

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Code availability (software application or custom code): If required.

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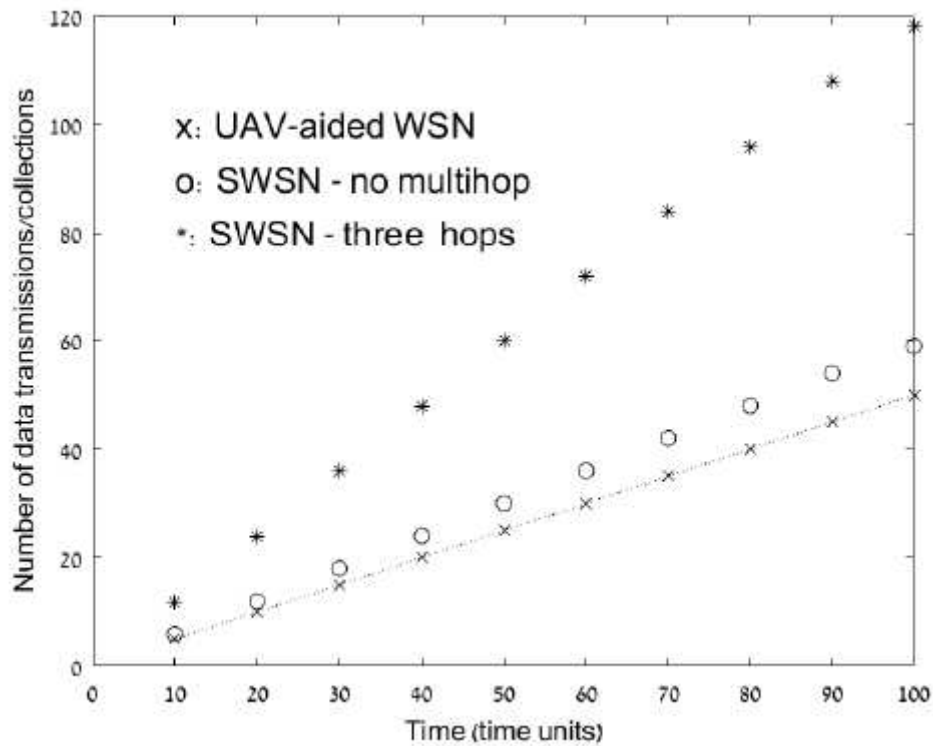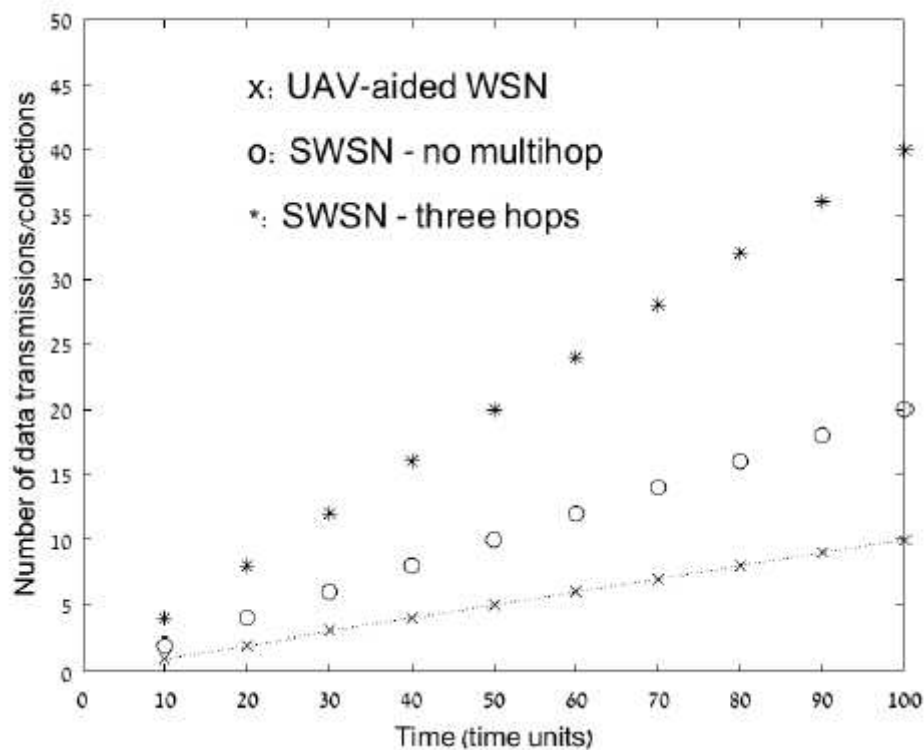
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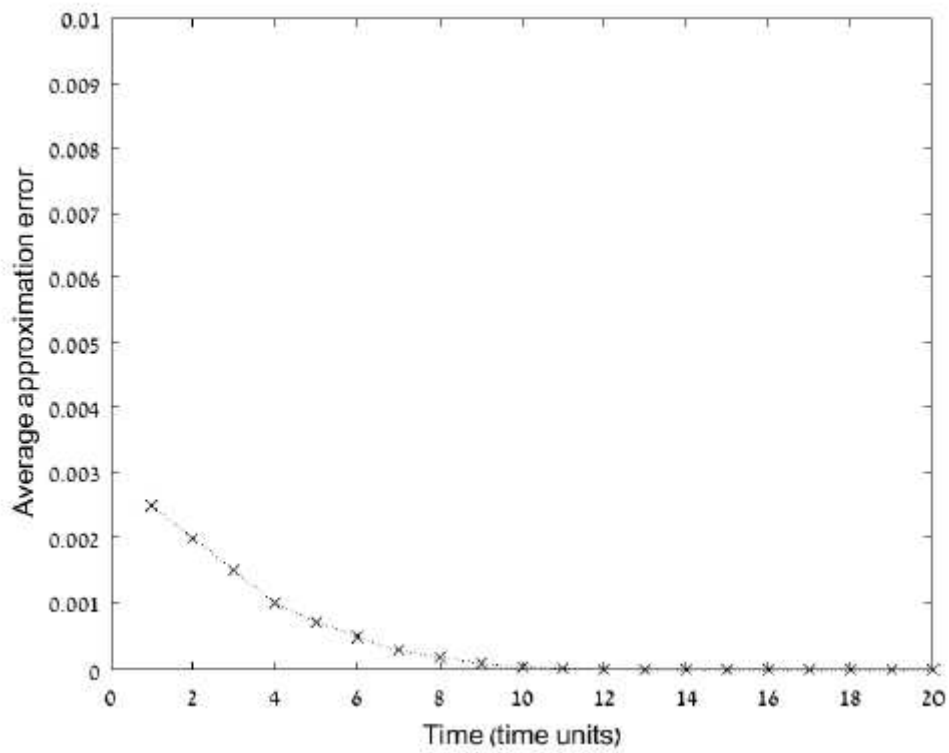
Figure 1

The quality of approximation, expressed by the average approximation error, as a function of time (in time units).

Figure 2

The average number of data transmissions/collections per SN, for a PWSN, versus transmitting WSN (TWSN) with no multi-hop transmission, and with three hops transmission per SN, as a function of time (measured in time units).

Figure 3

The average number of data transmissions/collections per SN, for a PWSN, versus TWSN, for the same data collection rate, as a function of time (measured in time units).