Flexibility of Decentralized Energy Restoration in WSNs

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Abstract. Wireless Rechargeable Sensor Networks (WRSNs) have become more and more popular thanks to the advances in wireless power transfer and battery material. The strategy followed by the charger to decide which sensor to be recharged next, is considered *effective* if only few sensing holes exist at any time, and their duration is short-lived. Ideally, the strategy will allow the system to be *immortal*; that is, all sensors are operational at all times. A recharging strategy is said to be *flexible* if it is effective for a wide range of parameters (i.e., for different applications).

In this paper, we analyze a simple decentralized recharging strategy which is based on local learning, operates without any a-priori knowledge of the network, has small memory requirements, and uses only local communication. We study the effectiveness and the flexibility of such a technique under a variety of ranges of the network parameters, showing its applicability to various contexts. We focus on three classes of applications that differ in network size (number of sensors), level of sensitivity of collected data, transmission rate, battery capacity, and type of mobile charger used to replenish energy. Our experiments show that in all these different settings, this simple local learning strategy is highly effective, achieving total immortality or near immortality in all cases.

Keywords: Adaptive · Decentralized · Recharging · Mobile charger · WRSN · Local learning

1 Introduction

1.1 Energy Restoration

Wireless sensor networks (WSNs) are used in a wide range of applications; they consist of small devices, called sensor nodes, deployed in a targeted area to monitor, collect, and report information on the surrounding environment. In the majority of applications, the sensors are powered by batteries of limited (usually small) capacity. When the battery becomes depleted, the sensor stops being operational, creating a sensing hole (and possibly a coverage hole) in the

L. Foschini and M. El Kamili (Eds.): ADHOCNETS 2020, LNICST 345, pp. 100–115, 2021.
https://doi.org/10.1007/978-3-030-67369-7_8

network. Unless remedial action is taken, eventually the entire network stops operating.

The earliest approaches to extend the WSN lifetime focused on reducing the energy consumption of the sensors (e.g., [6]); These approaches however only delay the inevitable demise of the network.

To prolong the life of the network almost indefinitely it is indeed necessary to restore the depleted energy in the network. Various approaches to energy restorations considered in the literature are *endogenous*, consisting of enhancing the sensors by adding capabilities that would enable them to recharge their battery. An example of such an approach is the proposal to provide the sensors with *energy harvesting* equipment to collect energy from surrounding resources [1,9,25]. This approach suffers from resource fluctuation and small harvested energy amounts that are not enough to fulfill sensors operations.

Another proposal has been to equip the sensors with *mobility* and location capabilities, so they can move to a recharging station when the battery level becomes too low, recharge, and then return (e.g., [24,32]).

All these proposals require sensor nodes of substantially increased complexity (and thus cost); this fact severely limits their feasibility and applicability.

An important popular alternative, that does not require more complex sensors, consists of using a mobile entity (robot, vehicle, etc.) that acts as a *mobile energy charger* (MC), moving in the environment and restoring the energy supply to nodes in need. This *exogenous* approach, intensively studied from a theoretical point of view, is becoming increasingly more practical and relevant due to the recent breakthrough in the area of *wireless energy transfer* technology by Kurs *et al.* [16,17]; once this technology becomes fully developed, the MC should be able to recharge a battery efficiently without the need of wires and plugs, with energy generated elsewhere.

1.2 Effectiveness, Immortality, and Flexibility

The idea behind this approach is simple: the mobile charger MC moves through the network recharging depleted nodes, with possible stops to an (exterior) recharging station to renew its own energy capacity (although most studies assume the latter to be infinite). The MC decides which sensor it should recharge next according to some strategy, with the objective of keeping the network functioning forever.

The *effectiveness* of a strategy is evaluated in terms of two measures: How many sensors are operational at any one time (called *operational size* or *coverage*), and for how long a sensing hole lasts (called *disconnection time*). The ideal situation, called *immortality* [29], is when the coverage is complete and disconnection time is nil; that is, when all sensors are operational at all times.

These two measures, coverage and disconnection time (and thus, the effectiveness), depend on a multitude of factors, including the number of sensors, the battery capacity, the size of the sensing area, and the power of the MC (e.g., speed, charging distance, charging time); these factors vary from one application to another, depending on the type of application. This means that the effectiveness of recharging strategies may vary greatly in different application settings. Hence another important measure of a restoration strategy is its *flexibility*, that is its capacity to be effective for a wide range of parameters, i.e., in several different applications.

1.3 Main Contributions

In this paper, we analyze the effectiveness in a variety of applications of the simple fully decentralized MC strategy introduced in [2] that, unlike previous strategies, is based on local learning, operates without any a-priori knowledge of the network, has small memory requirements, and uses only local communication.

We focus on three classes of application settings. The first class includes applications characterized by a small number of sensors deployed in a relatively small area, low data sensitivity, and low transmission rate; it is well suited for a robot charger. The second includes applications characterized by a moderate number of deployed sensors, highly sensitive data, and a high transmission rate; it describes settings suitable for both robots or vehicles. The third class, which is more suitable for a vehicle charger, includes applications characterized by a large number of deployed sensors in large areas, and low transmission rate.

In all cases, we evaluate the effectiveness of the strategy in terms of *operational size*: the number of sensors that are maintained operational at any given time, and *disconnection time*: the time from the moment a sensor becomes no longer operational to the time when the MC serves it.

We show that in all three settings the system reaches immortality (all nodes are always operational), or near immortality (90% of the nodes are always operational and if a node becomes non-operational it does so only once, and never for more than 1% of the network lifetime). In other words, in spite of its simplicity, the strategy is highly effective in all three distinct classes of application settings, showing its flexibility.

The paper is organized as follows. The next subsection contains a concise review of related work; Sect. 2 introduces the model; the proposed strategy is described in the Subsect. 2.2; the experimental results and their discussion are contained in Sect. 3; Sect. 4 concludes this paper.

1.4 Related Work

Several strategies have been proposed, studied and analyzed. In the following, we do not consider *off-line* strategies (i.e., those that assume knowledge of the future events) but only *online* strategies.

A popular approach used in the existing work is based on *centralized* strategies where the sensors report their energy levels (directly or through a base station) either at regular intervals of time, or when their battery level reaches a certain threshold. This is the case, for example, of *on demand* policies (e.g., see [18,26,33]). Furthermore, centralized algorithms are used to solve optimization problems requiring global system information (e.g., [10,18,26,29,30,33]). In particular, in [33] the sensors report their energy levels periodically, and the recharging order is computed by the MC using a centralized algorithm which solves a global optimization problem; in [26], a centralized solution is provided to maximize the ratio of recharging time to vehicles idling time; in [18], each node periodically sends its energy data (e.g., energy level, consumption rate, etc.) to the base station that, based on this data, centrally determines the charging schedule and communicates to the MC through long range radio; a network utility maximization problem is solved in [10]. Other centralized policies have been studied in [12,15,23].

Some *decentralized* strategies have also been devised; in [21], the authors aim to maximize the sensors' lifetime by minimizing the charging tour length and maximizing the charging utility gain; at the same time, the mobile charger receives a reward for every successful recharging process. The authors assume that the mobile charger has finite energy and the maximum number of served requests is limited; in [3], the authors proposed that the network has limited energy and investigated in the optimal ratio of energy assigned to the mobile charger relative to energy assigned to the sensors. Also, they tested full charging versus partial charging. Finally, they tested their hypothesis under several trajectories.

However, the energy restoration process is limited in the sense that there is a bound on the total amount of energy that can be put into the system; in [8] a decentralized energy restoration strategy based on a global circular order of the nodes. Their findings proved the importance of giving a decentralized approach. However, they assumed that the mobile charger follows a trajectory known a-priori. Recently, we have proposed a simple fully decentralized MC strategy that, unlike previous strategies, is based on local learning, operates without any a-priori knowledge of the network, has small memory requirements, and uses only local communication [2].

Finally, some work has considered the use of multiple MCs in various settings; see for example [7,19,22,28].

Let us remark that, to the best of our knowledge, the effectiveness measures considered here as well as the notion of flexibility, have not been explicitly considered in the literature. The only exceptions are [2,8], where however the focus is only on the effectiveness of the proposed strategies and the analysis is limited to restricted cases.

2 Model and Strategy

2.1 The Network

Let $\mathcal{S} = \{s_1 \ldots, s_n\}$ be a set of n *sensor nodes*, distributed randomly in a two-dimensional square area. Each node has sensory equipment that allows it to monitor its surroundings; it also has provision for wireless communication. The sensors are homogeneous, and the batteries have the same capacity E_{max};

however, depending on their activities, sensors might consume their batteries, and thus deplete their batteries, at different rates.

In this paper, we use the power consumption model of [29] (also employed in [5,14]). Let $P(s)$ denote the energy consumption rate at sensor node $s \in \mathcal{S}$; $P(s)$ is given by the following equation:

$$P(s) = \rho \cdot \sum_{p \in \mathcal{S}}^{p \neq s} f_{j,s} + \sum_{j \in \mathcal{S}}^{p \neq s} C_{s,j} \cdot f_{s,j} + C_{s,B} \cdot f_{s,B} \tag{1}$$

where: $\rho \cdot \sum_{p \in \mathcal{S}}^{p \neq s} f_{j,s}$ is the reception power consumption, ρ is the energy consumption for receiving one unit, and $f_{j,s}$ is the flow rate between node j and node s; $\sum_{p \in \mathcal{S}}^{j \neq s} C_{s,j} \cdot f_{s,j} + C_{s,B} \cdot f_{s,B}$ is the transmission power consumption, where $C_{s,j} = \beta_1 + \beta_2(d_{s,j})^{\alpha}$, where β_1 and β_2 are distant dependent constants, $d_{s,j}$ is the transmission distance, and α is the path loss index, $C_{s,B}$ is the energy consumption for transmitting one bit of data between node s and base station B. Since sensing the environment requires negligible energy compared with sending and receiving operations, it is considered null. All interactions assume the existence of an ideal MAC Layer, which provides a reliable wireless communication channel by guaranteeing collision-free access to the medium and eliminating interference due to simultaneous transmissions.

Any sensor where the current energy level L of its battery is below a predefined threshold τ_1 is considered in need of recharge and is said to be *at risk*. When its level falls below a predefined threshold $\tau_2 < \tau_1$, the sensor becomes *non-operational*: it stops its sensing activities, thus creating a sensing hole in the network, and it uses its remaining energy only for the limited local communication required to be recharged.

A special mobile entity, called *Mobile Charger* (MC), is deployed in the system to re-charge the sensors in need. The MC is equipped with power transfer technology, and it can charge a sensor when in its proximity. The MC is equipped with a large battery of capacity E_{MC} (initially fully charged), this capacity is used for moving and recharging purposes in the robot-based MC, while it is used for only recharging sensors in the Vehicle-based MC.

The capacity is assumed to be sufficient to charge all the sensors at least once. When the MC battery reaches a given threshold, the MC travels back to the *Service Station* (SS). The SS has fast charging equipment or battery replacement equipment to guarantee fast service time. The SS might be connected to the electricity grid or might have large energy storage that stores energy from various renewable or nonrenewable energy sources. After its battery is recharged or replaced, the MC continues the sensors' charging process.

The decision of which sensor should be recharged next defines the *recharging strategy* employed. The objective of the recharging strategy is to keep the network functioning forever, keeping the number of operational sensors at any one time as large as possible, and the duration of sensing hole as small as possible. Hence the *effectiveness* of a recharging strategy $\mathcal{A}$ is measured in terms of the number of operational sensors and the duration of sensing holes. More precisely, the *operational size*, or *coverage*, at time t under $\mathcal{A}$ (denoted by $Coverage(\mathcal{A}, t)$) is the number of operational nodes at that time; note that the coverage implicitly measures the number $Holes(\mathcal{A}, t) = n - Coverage(\mathcal{A}, t)$ of the sensing holes at time t. The *disconnection time* for node x at time t under $\mathcal{A}$ (denoted by $Disconnect(\mathcal{A}, t, x)$) is the amount of time x had been inactive when last serviced by the mobile charger before or at time t; that is, it measures how long the sensing hole created by x lasts.

Given a recharging strategy $\mathcal{A}$ for the sensor network $\mathcal{S}$, the network achieves *complete immortality* if, within finite time (i.e., after a transient), 100% of the sensors are operational at all time. We also say that $\mathcal{S}$ achieves *near immortality* under $\mathcal{A}$ if, within finite time (i.e., after a transient), 90% of sensors are operational at any time *and* the total disconnection time of a sensor is at most 1% of the network's lifetime.

2.2 The Charging Strategy

We describe the *Local-Learning* fully decentralized recharging strategy used in this paper. In this strategy, the MC starts without any a-priori knowledge of the sensors' location, their initial charges, nor their consumption rates.

Instead of letting the nodes report their energy levels (directly or through a base station) periodically or when the battery level reaches a certain threshold (e.g., *on demand* policies), the MC gathers the battery energy levels of the neighbouring nodes as it moves through the network. This eliminates long distance communications between the MC and the nodes, without need for clustering, cluster management, or cluster-head elections.

The collected data is used by the MC to learn online the dynamics of the network nodes and to build a fully dynamic charging schedule. More precisely, the data is used by the MC to determine, using a simple heuristic, to which node it should move to recharge next. This mechanism provides a continuous gathering of energy information and, in turn, a fully dynamic energy depletion prediction.

In more details, the algorithm behaves as follows. Upon start-up, the MC makes two rounds of exploration of the network, collecting data from the encountered nodes and their neighbours, servicing those that need recharging. Since the MC is initially located close to the BS, the MC communicates with the BS to collect all the available information about the one-hop nodes that communicate directly with the BS, and computes the distance to each of those nodes.

The MC visits the sensors in a greedy fashion, closest unvisited neighbor first, and backtracking once all the sensor's neighbors have been visited. In each visit, the MC records the location of each sensor, its battery level $L_1(s)$ (resp. $L_2(s)$), the current time $t_1(s)$ (resp. $t_2(s)$) for the first (resp,. second) visit, and neighbors' locations; if the MC encounters any sensor with energy $L(s) < \tau_1$, it recharges it. By the end of the two traversals of this startup stage, the MC has constructed a vector of size n with the collected information of the sensors, providing a complete map of the network as well as the means to estimate the future needs of the sensors. The consumption rate $\delta(s)$ of each sensor S is computed as $\delta(s) = (L_2(s) - L_1(s))/(t_2(s) - t_1(s))$. Next, the MC calculates the traveling time to all sensors. Let t be the current time, $d(s,t)$ be the distance from MC to node s at time t, and V be the speed of MC. Then, the time that it would be required for MC to reach s is $\Delta t = d(s,t)/V$. Finally, the calculated consumption rate and travel time are used to estimate the Expected Energy $L_{Exp}(s)$ of the sensor s at time $t + \varDelta t$ as follows:

$$L_{Exp}(s) = L_2(s) - \delta(s) \cdot (t - t_2(s) + \varDelta t)$$

The next sensor to be charged is chosen to be the one with lowest expected energy: $\min_{s \in \mathcal{S}}\{L_{Exp}(s)\}$.

This policy is used for all the subsequent rounds (the *charging rounds*): the MC continues to move greedily, to record the current state of charge values, to record the current time stamp and to update the expected energy values of each sensor it encounters, so that the charging schedule is always based on the most up-to-date information.

Preliminary results have shown that such a strategy is highly effective [2], achieving the same results as those in the specific centralized settings of [13,29].

3 Results and Discussions

The goal of this study is to determine the *flexibility* of this simple and efficient energy restoration strategy; that is, whether it would be highly effective in settings arising in different types of applications. To this end, we have carried out a large number of experiments under a variety of ranges of the network parameters, and analyzed the results in three classes of applications.

Perhaps surprisingly, we find that the strategy is highly effective, achieving total immortality or near immortality in all cases.

In this section, we describe the experimental setup and the main application settings considered. We then present and analyze the results.

3.1 General Parameters and Experimental Setting

To analyze the effectiveness of the Local-Learning strategy and evaluate its flexibility, we consider different network sizes, varying the number n of sensors between 100 and 600 ($n = 100, 200, 300, 400, 500, 600$), deployed in a square area of variable size (from 200 m $\times$ 100 m to 1000 m $\times$ 1000 m). We use three types of sensor battery capacities (780 mAh/1.2 v, 1.2 Ah/2.5 v, 1.2 Ah/3.7 v), considered in [28,29,34], which are equivalent to (E_{max} = 3.37 KJ,10.8 KJ,15.98 KJ) respectively. The power consumption coefficients (Eq. 1) are $\rho = 50$ nJ, $\beta_1 = 50$ nJ/b, $\beta_2 = 0.0013$ pJ/(b.m^4), and $\alpha = 4$ (see [11,13,26,29]). The initial state of charge of each sensor is a random ratio (20%–70%) of E_{max}; a sensor is considered non-operational if the state of charge is below 5% of E_{max}. At each time unit (1 min of 6 months of simulated time), a sensor sends and receives a random number of packets of size [1–10]Kbit.

The MC consumes 5 J/m for moving, and radiated power with efficiency $\eta = 95\%$ [13]. We consider two charging times ($\gamma = 30, 78$ [29,34]) expressed in minutes. To reflect different types of mobile chargers (vehicle or robot), we consider different speeds (v = 1 m/s, 2 m/s, 5 m/s) and battery capacities (E_{MC} = (216, 770) KJ).

For the experimental evaluation, we use a discrete event simulator developed in MATLAB. For each combination of the values of the parameters, we have run 100 executions. In each execution, the simulated time is 6 months, with time unit 1 min. In each execution, we compute the effectiveness of the Local-Learning strategy by computing the *average* operational size and *average* disconnection time over the simulated time.

3.2 Applications and Settings

In this work we particularly focus on three classes of applications that differ in network size (the number of sensors), level of sensitivity of collected data, transmission rate, battery capacity, and type of MC used to replenish energy.

The first class, *APP1*, contains applications where the number of sensors is small, sensors have small batteries, the sensitivity of the data is low, transmission rate is low, and a robot is more appropriate as a MC. This class includes for example the application that measures soil humidity [27], where 100 sensors or less are deployed, the collected data is not sensitive so the transmission rate is low, the coverage area is rather small (200 × 200 m); because of the size and the nature of the area in this setting a robot is an appropriate choice for MC.

In the second class, *APP2*, which includes the application of the tracking intruders movement [20], the collected data is highly sensitive, the number of sensors is moderate, and the transmission rate is high. For example, in [20], 200 sensors were deployed in a small area of (200 × 100 m); depending on the combination of the various parameters, both robot and vehicle could be suitable choices for the MC.

In the third class, *APP3*, which includes the barrier intruder detection application [31], there is high sensitivity of collected data, the number of sensors is large, the transmission rate is small (e.g., data are sent only if an intruder crosses the borders), and the more suitable MC is a vehicle or a drone. For example, [4] deploys 300–600 sensors in area of 400 × 400, while [31] deploys 200–400 sensors in an area of 800 × 400 m. In our experiments, we consider the worst setting: the largest area (800 × 400 m) and the largest number of sensors (300–600).

Table 1 indicates the specific ranges of parameters associated to these three application classes.

3.3 Experimental Results

In this section we describe the performance of the system in the three considered settings.

Table 1. Application classes

	APP1	APP2	APP3
n	100	200–300	300–600
Area	200 m × 200 m	200 m × 100 m	800 m × 400 m
E_{max}	3.37 kJ	(10.8, 15.98) KJ	(10.8, 15.98) kJ
τ	674 J	2160, 3196 J	2160 J, 3196 J
τ_1	168 J	540 J, 799 J	540 J, 799 J
E_{MC}	216 kJ	216 kJ, 770 KJ	770 KJ
v	1 m/s, 2 m/s	1 m/s, 2 m/s, 5 m/s	5 m/s
E_{Move}	5 J/m	5 J/m	5 J/m
γ	78 min	{30, 78} min	30 min
λ (Kbit)	1–6	1–10	1–8

Robot MC vs. Vehicle MC. In the experiments, we use two types of mobile chargers with different characteristics, a robot-based MC and a vehicle-based MC. In the robot-based MC, the MC battery capacity is small and the charging time is high since the robot has limited space and weight to carry. On the other hand, in the vehicle-based MC, we have plenty of space, and the vehicle can carry more advanced equipment as well as a larger battery; thus, the charging time is short and the MC battery capacity is large.

In particular, for vehicle-based MC, we considered a battery capacity of 770 KJ, a speed of 5 m/s, and a charging time of 30 min. On the other hand, for robot-based MC we assumed a battery capacity of 216 KJ, a speed of 1,2 m/s and a charging time of 78 min.

APP1

The ideal outcome of an energy replacement strategy for an MC is to ensure that the networks becomes immortal; that is, no sensor ever becomes non-operational, even for a small amount of time.

Interestingly, the experimental results show that the Local-Learning strategy achieves precisely this outcome for all networks whose settings are in the application class *APP1*. More precisely, for all such network settings, after the initialization stage (without any knowledge of the network), the Local-Learning strategy keeps the network perpetually operating with no sensor ever depleting its battery (see Fig. 1). In other words, the Local-Learning strategy achieves *complete immortality* for the entire class *APP1*.

APP2

For this class of applications, where the area covered by the sensors is of medium size, both a robot and a vehicle could be suitable. For the setting corresponding to the use of a vehicle-based MC, the Local-Learning strategy achieves *complete immortality*. Indeed, as shown in Fig. 2-(a), in this case, no sensor ever becomes non-operational.

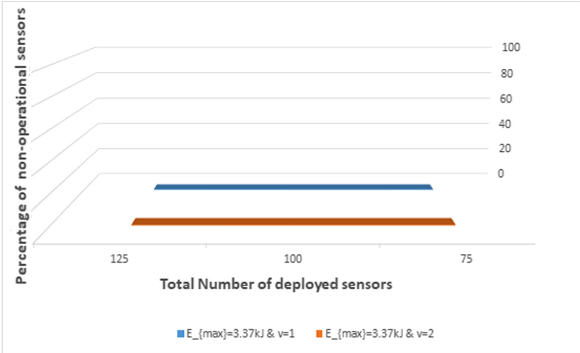

Fig. 1. APP1: Percentage of non-operational sensors.

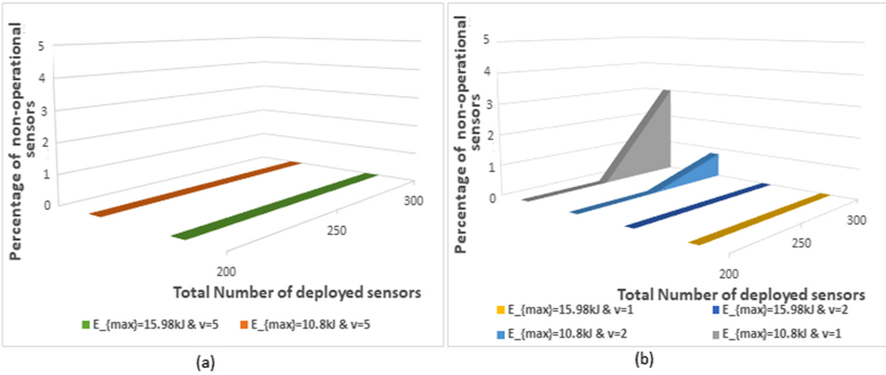

Fig. 2. APP2: Percentage of non-operational sensors (%)

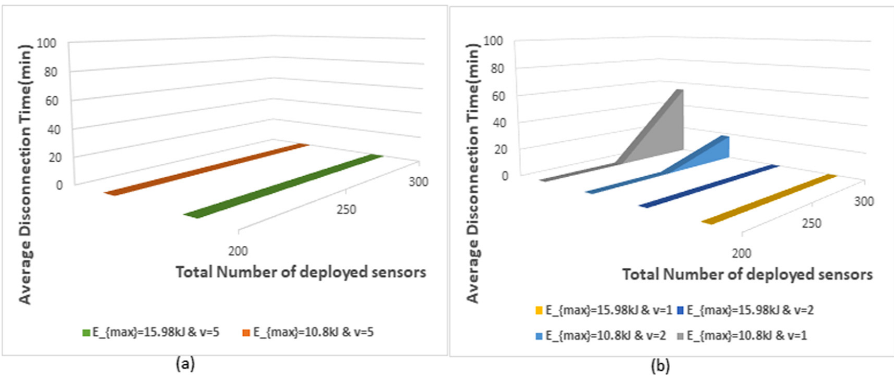

Fig. 3. APP2: Average disconnection time (minutes)

The results for a robot-based MC are also very good. Figure 2-(b) shows the percentage of non-operational sensors using a robot-based MC for various combinations of speed and risk threshold and we can observe that the non-operational sensors never exceed 6% of the total number of sensors and the percentage is often much lower than that. In correspondence to these settings, Fig. 3 shows that the average disconnection time for a sensor that gets depleted is never more than 1 hour.

We also observed how many times a sensor can become non-operational because of a depleted battery noticing that no sensor becomes non-operational more than once. That is, when the MC is a robot, over the entire simulated period of 6 months,

Summarizing, for all network settings in *APP2*, after the initialization stage (without any knowledge of the network), the Local-Learning strategy let the network achieve *complete immortality* if the MC is a vehicle, and *near immortality* when the MC is a robot.

APP3

Also for this class of applications, which are vehicle-based, the results applying the Local-Learning strategy are excellent. We obtain *complete immortality* for all combinations of parameters, with one exception. The exception is when the number of sensors is the highest (600).

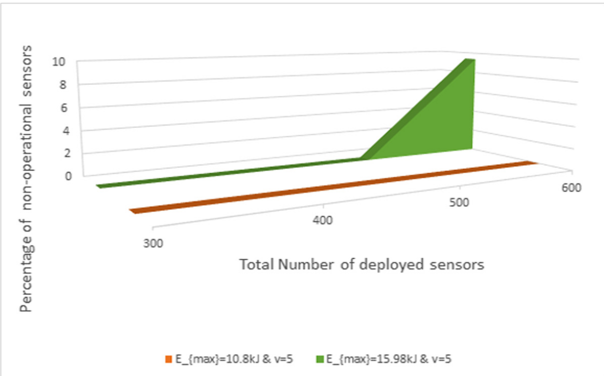

Fig. 4. APP3: Percentage of non-operational sensors for various sensors' battery capacities.

In correspondence of this setting, during the simulated lifetime (6 months), at any time, no more than 10% of the sensors become non-operational (see Fig. 4). Furthermore, a sensor never becomes depleted more than once, and the average disconnection time is never more than 5 h (see Fig. 5). In other words, in this case, the network achieves *near immortality*.

Summarizing, for all network settings in *APP3*, after the initialization stage (without any knowledge of the network), the Local-Learning strategy let the network always achieve *near immortality* and often *complete immortality*.

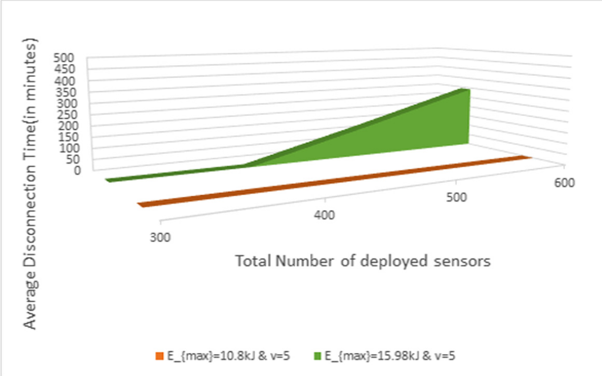

Fig. 5. APP3: average disconnection time using a robot MC.

3.4 Additional Results and Insights

To test further the flexibility of our approach, we have run experiments varying some of the parameters also beyond the three classes of applications. In particular, we tested $E_{max} = 3.37$ KJ, $E_{max} = 10.8$ KJ, $E_{max} = 15.98$ in all three settings, we employed $\gamma = 30$ min and $\gamma = 78$ min, under the worst conditions of all the other parameters, and we extended the size of the area where the sensors are deployed. Simulating the strategy under this wider range of variables leads to the following observations:

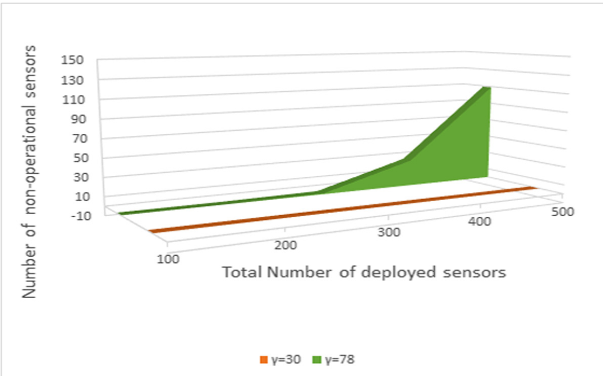

Fig. 6. Number of non-operational sensors with various charging rates: $E_{max} = 3.37$ kJ, $v = 1$, $\lambda = (1–10)$ Kbit, area of 1000 m $\times$ 1000 m

- The smaller the recharging time γ, the better the performance of the strategy. This is not surprising since less recharging time gives the MC more time to visit all the sensors before they get depleted. With recharging time up to $\gamma = 30$ min our approach achieves immortality even under the worst condition of the other parameters (large networks, small sensor battery, low MC speed), as shown in Fig. 6.
- Clearly, larger sensor battery capacities lead to better performance; from our experiments, however, we observe that $E_{max} = 10.8$KJ is the best choice of battery capacity among the ones tested because such batteries are cheaper than the ones with capacity $E_{max} = 15.98$ KJ, and its use achieves almost the same results as the ones obtained with $E_{max} = 15.98$. Decreasing the capacity, we start observing a decrease in performance; in fact, with $E_{max} = 3.37$ KJ we have an increase in the number of non-operational sensors (although their disconnections are still short-lived).
  Under the most unfavorable choice of parameters the increase becomes noticeable, while still not excessive and always below 14%; this happens in correspondence of transmission rate λ = (1–10) Kbit, charging time $\gamma = 78$ m, and a large area of 1000 m $\times$ 1000 m (see Fig. 7).
- All three applications scenarios have been simulated also in larger areas without any decrease in performance. In fact, as Fig. 8 shows, the percentages of non-operational sensors is always below 10%, even in the worst possible condition of battery capacity.

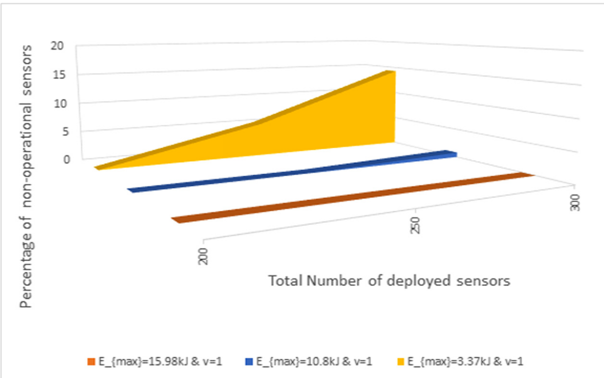

Fig. 7. Percentage of non-operational sensors with various E_{max}: λ = (1–10 Kbit), γ = 78 min, area of 1000 m $\times$ 1000 m.

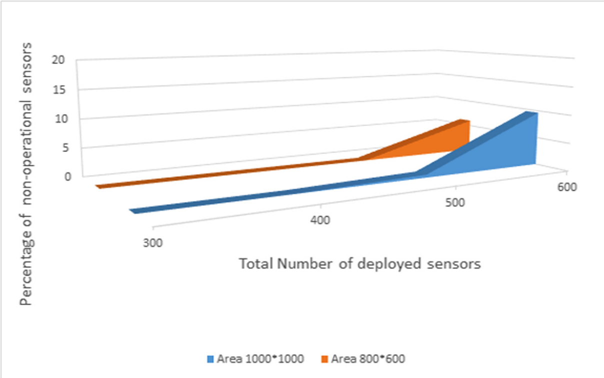

Fig. 8. APP3: Percentage of non-operational sensors in various areas with λ = (1–6 Kbit), $E_{max} = 3.37\,\text{kJ}$, $\gamma = 30\,\text{min}$.

4 Conclusions

In this paper we considered the problem of recharging WSN using a mobile charger. In particular, we studied the applicability of a simple decentralized local learning strategy on a wide range of application parameters: number of sensors, size of the area in which they are deployed, and mobile charger characteristics (speed, battery capacity, charging time, etc.). We found that in all those settings, the strategy achieves complete immortality, or near immortality with the occasional disconnections being very short-lived. This shows the high flexibility of this strategy to changes in the system parameters. The success of the method is due to the ability of the mobile charger to "learn" the global distribution of battery discharges; we are now studying its behavior under variations in the battery discharging patterns, to assess its adaptability to changes. An open direction of investigation is the analytical study in support of the experimental results.

Acknowledgment. I would like to thank Prof. Nicola Santoro and Prof. Paola Flocchini for their helpful guidance and discussions.

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