A Lightweight Classification Algorithm for Energy Conservation in Wireless Sensor Networks

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Abstract—**Classification of sensor nodes can be used as a technique for conserving energy and prolonging the lifetime of a wireless sensor network (WSN). In this paper, we present a new algorithm of lightweight and dynamic classification. By this algorithm, energy consumption is reduced while providing a full coverage, which is an important network parameter in WSNs. Moreover, node classification is adaptive to topology changes and has no constraint on routing protocols and hardware. Based on sensors residual energy, they are classified as *essential* and *non-essential*, and rotated dynamically. Essential nodes send their measurements to the sink, whereas, non-essential ones do not send new data and receive queries from the sink. This reduces transmitting and receiving energy of non-essential nodes and regulates data traffic. Further, our mechanism may provide location-based tunable redundancy, e.g., if redundant data is needed from a specific region, the sink may query the corresponding essential nodes to activate non-essential ones in that region. We analyze the complexity and energy consumption for the scenario where nodes are randomly deployed in a given region. Analysis, supported by extensive simulation in ns2, show that energy consumption due to communications can be reduced in proportional to the ratio of essential nodes and fairly distributed among sensors by rotation.**

I. Introduction

In a typical wireless sensor network (WSN), many sensor nodes, each having limited battery power, monitor the events of interest and send their measurements to the sink [1]. In many applications, sensor nodes are densely deployed and transmit their data to the sink in an event-driven or continuous manner. Sink, the gateway node, collects received data and sends query or update messages to the sensors on-demand. For WSNs, one of the key factors in extending the functionality and the accuracy of applications is network lifetime, which can be prolonged by energy conservation and fair energy consumption among nodes.

Many research works have addressed energy conservation from different viewpoints, based on different operation of sensors. A sensor node consumes energy due to (i) transmitting, receiving, forwarding and processing data packets, and (ii) idle listening and overhearing control packets [17]. Energy consumption due to idle listening and overhearing can be reduced by MAC protocols having periodic sleep intervals [16]. Also, topology control mechanisms have been proposed to provide sleep schedules which are highly dependent on routing protocols [4]. Further, improving energy-efficiency is considered as a factor in various routing protocols [3], cluster-based topology control mechanisms [17], and power-control mechanisms [5].

In energy-efficient topology control, network topology is determined by the connectivity. For example, in [15], sensing area is divided into grids and one sensor is active for each grid, while, other sensors are put into the sleep mode. In sleep mode, sensors turn their radio off which may highly affect routing operation. In addition, there exist attempts to use clusters for an energy-efficient communication. In [8], a distributed clustering protocol has been presented where cluster heads coordinate the communication inside and outside of a cluster, and cluster heads also aggregate the received information. Another topology control mechanism has been presented in [10], where a network consists of sensor clusters and base stations optimally placed for maximizing network lifetime. Within each cluster, an application node receives data from sensors, creating a comprehensive-view, and forwarding it to the base station. Usually, clustering systems require more powerful nodes to be cluster heads, since their computational requirements and the consumed energy are higher. Furthermore, scheduling of nodes based on sensing coverage is also a technique for energy conservation, in which only the active sensors in a set are responsible for monitoring while others are put into sleep mode [2], [7]. However, in case of unexpected node failures, all sets should be reformed.

In this paper, we propose a lightweight classification mechanism which reduces transmitting/receiving energy consumption, while decreasing the traffic load in a tunable manner. The main features of this mechanism are being dynamic and independent of underlying routing protocols with no extra hardware requirements, e.g., cluster heads. In particularly, we design a greedy-based algorithm that considers energy consumption as the *cost* in selecting *essential* (E) nodes with higher residual energy which can monitor the entire sensing field. Thus, our algorithm aims to minimize the *total cost* of sensors that cover the entire sensing field. In each step, an unused sensor, covering the largest remaining area and having higher energy, is chosen. The algorithm mainly runs on the sink where locations of the sensors are known initially via any lightweight localization technique used in wireless networks [6]. Moreover, we rotate the E-nodes dynamically to balance consumed energy. In every update interval, the sink re-performs the weighted algorithm to form a new set of E-nodes by minimizing the total cost. Thus, an E-node, whose energy consumption is high, might be a *non-essential (N)* nodes for the next update interval. This dynamic rotation also helps handling the topology changes due to unexpected node failures. As a result, we consider both conserving energy at each node and balancing energy consumption among nodes by dynamic rotation, thus prolonging the lifetime of each sensor. Having such a mechanism, in addition, allows for tunable redundancy when necessary. For example, sink may send a query to the E-nodes located in a specific region to increase the redundancy.

The remainder of the paper is organized as follows. Section II presents the problem formulation. We describe the proposed algorithm in detail in Section III, and present the analysis of algorithm complexity as well as energy consumption in Section IV. Following, simulation results are presented in Section V and conclusions are drawn in Section VI.

II. Problem Formulation

A. Network Description

Let $S = \{s_1, s_2, s_3, \ldots, s_N\}$ be the finite set of sensors which are distributed randomly in a two-dimensional area $\mathbf{A}$. Each sensor s_i has a unique *identifier* (such as MAC address). We also assume that each node is equipped to learn its location information via any lightweight localization technique for wireless networks [6]. Therefore, all sensor nodes and the sink know their location coordinates (x_i, y_i) and *sensing range* r_i. We assume that all nodes have similar processing and communication capabilities and multi-hop data transmissions.

The *sensing region* R_i of a node s_i is the circular area with its center at (x_i, y_i) and radius of r_i. A subset of sensors, $\mathbf{C} \subseteq S$ is called a *coverage set* if the union of the sensing regions of the $s_i \in \mathbf{C}$ covers the entire field $\mathbf{A}$, that is $\mathbf{A} \subseteq \bigcup_{s_i \in \mathbf{C}} R_i$.

The sensors are classified into essential (E) nodes and non-essential (N) nodes. The classification algorithm is proceeded by finding a *coverage set*, denoted by $\mathbf{C}$. Let $\mathbf{C}$ be the coverage set with number of sensors $\mathcal{N}$, i.e., $\mathcal{N} = ||\mathbf{C}||$. We consider a sensor node to be an E-node in $\mathbf{C}$ if $s_i \in \mathbf{C}$. This E-node referred to as $s^{(E)}$. Otherwise, it is non-essential node, $s^{(N)}$. The coverage set is valid in a time interval called *update interval*, denoted by $T_{\triangle U}$. In other words, the coverage set is updated periodically for every $T_{\triangle U}$.

B. Energy Model

We focus on reducing a dominant factor in energy consumption, *communication*. Power consumption of a sensor node is a function of reception, $p_r(t)$, transmission, $p_t(t)$, and forwarding, $p_f(t)$ power consumption [10], which is given by:

$$p(t) = p_r(t) + p_t(t) + p_f(t), \tag{1}$$

where

$$p_t(t) = r_t(t) \cdot E_b^t, \quad \text{and} \quad p_r(t) = r_r(t) \cdot E_b^r. \tag{2}$$

TABLE I

Notations

Symbol	Description
S	The set of sensors in the WSN
C	Coverage set
A	Sensing field
$s_i^{(E)/(N)}$	A sensor node at (x_i, y_i)
r_i^s	Sensing range of node s_i
R_i	Sensing region of node s_i
r_i^t	Transmission range of node s_i
$e_i(t)$	Residual energy of node s_i at time t
$e_i(0)$	Initial energy of node s_i
$p_i(t)$	Power consumption of node s_i in time t

In the above equation, $r_t(t)$ is the transmission rate at which the sensor transmits its measurements to the sink node; $r_r(t)$ is the rate of receiving data from the sink node; E_b^t and E_b^r are transmission and receiving energy per bit respectively, depending on modulation and coding schemes [12]. Power consumption due to forwarding, $p_f(t)$, at intermediate nodes, is the summation of receive and transmit power consumptions at rate $r_f(t)$, which is the rate a sensor forwards data.

$$p_f(t) = r_f(t) \cdot (E_b^t + E_b^r). \tag{3}$$

Therefore, residual energy of a sensor s_i at time t, can be calculated by

$$e_i(t) = e_i(0) - \int_0^t p(t)dt, \tag{4}$$

where $e_i(0)$ is the initial energy of the sensor.

Next, we will explain the classification algorithm for selecting essential nodes having higher residual energy in detail.

III. Classification Algorithm

We propose a weighted greedy algorithm to classify the sensors as essential (E) nodes and non-essential (N) nodes so that *E-nodes* will be sufficient to detect all events of interest in the entire sensing field. As a result, *N-nodes* may be set as passive, thus not sending new measurements until they are activated by an E-node or become an E-node. In this way, traffic generated by the sensors is regulated, reducing the transmission/reception and processing energy consumption of nodes. For instance, let us consider a fire monitoring application, where several sensors are deployed at a wildland fire site by airdrop or by workers on the ground. Sensors are responsible for reporting the fire alarms to the sink node periodically. Instead of sending reports from all sensors, E-nodes can monitor the whole site will send their reports.

To select the set of E-nodes, we attempt to find a *coverage set*, denoted by $\mathbf{C}$, to which E-nodes belong. In order to choose the coverage set, an ideal solution is to find the *minimum* number of sensors as a coverage set that covers the entire field. However, this problem is NP-hard, similar to the well-known set cover problem. The goal of the set cover problem is to cover a set with the smallest possible number of subsets given a ground set of elements [11]. Therefore, we use a greedy approach for *approximating coverage set*, running in polynomial time.

Several works have addressed the problem of finding near-optimal coverage in WSNs [7]. In [7], similar greedy approach is used to find a connected set of sensors whose sensing regions cover the sensing field. However, in our greedy algorithm, residual energy of nodes is considered since prolonging the network lifetime is the ultimate goal. We define an *effective cost* function for a sensor indicating the consumed energy over the uncovered area that can be monitored by this sensor. Then at each step, the sensor having the minimum effective cost is chosen as an E-node. This allows us to *minimize the overall cost* while covering the sensing field. Our algorithm of finding the coverage set is given by algorithm in Fig. 1.

In the algorithm, we first define a cost function $w(s_i)$ that represents the consumed energy by sensor s_i such that

$$w(s_i) = 1 - \frac{e_i(t)}{e_i(0)}. \tag{5}$$

The objective is to find a coverage set $\mathbf{C}$ and minimize the total cost of selected sensors, denoted by $Cost(\mathbf{C}) = \sum_{s_i \in \mathbf{C}} w(s_i)$. In each step, our algorithm (Fig. 1) selects one node from the unselected sensors which has the minimum *effective cost*:

$$cost_{eff}(s_i) = \frac{w(s_i)}{(R_i \cap A)/R_{\mathbf{C}}}, \tag{6}$$

where R_i is the sensing region of sensor s_i and $R_{\mathbf{C}}$ is the total region covered by the sensors in $\mathbf{C}$. In other words, in each step we choose the minimum cost over the maximum uncovered sensing area, where $(R_i \cap A)/R_{\mathbf{C}}$ represents uncovered sensing area of sensor s_i in terms of square meters.

Input: $S = \{s_1, s_2, s_3, \ldots, s_N\}$ is the set of sensors distributed randomly in a two dimensional area $\mathbf{A}$.
A sensor has s_i = (r_i, R_i, $w(s_i)$, (x_i, y_i)) where
r_i : the sensing range,
R_i : the sensing region,
$w(s_i)$: cost which represents consumed energy,
(x_i, y_i) : location coordinates.
Output: Coverage set, $\mathbf{C}$, minimizing total cost.

I.Initialize
  $\mathbf{C}$:= $\emptyset$
  Let $R_{\mathbf{C}}$ be total sensing region of $\mathbf{C}$
II.Repeat
  Let $S/\mathbf{C} = \{s_1, s_2, \ldots, s_n\}$ be the candidates,
  min_cost := 0;
  for each $s_i \in S/\mathbf{C}$
    Calculate the cost effectiveness of s_i
    $cost_{eff}$:= $\frac{w(s_i)}{(R_i \cap A)/R_{\mathbf{C}}}$;
    if ($cost_{eff} \leq$ min_cost)
      min_cost := $cost_{eff}$;
      $temp$:= s_i;
    end if;
  end for;
  $\mathbf{C}$:= $\mathbf{C} \cup temp$;
Until $\mathbf{A} \subseteq R_{\mathbf{C}}$

III.Finalize
  Return $\mathbf{C}$;

Fig. 1. Algorithm of Selecting E-Nodes.

Fig. 2 (a) shows an example sensor network where sensors deployed randomly on a rectangular area $\mathbf{A}$. The sensing region boundary of each node is plotted with dashed-circles around the sensors. Each sensor may have different sensing range. When the algorithm is finished, the union of sensing regions of selected E-nodes should cover the sensing field. Therefore, we guarantee that (i) when an event occurs, it is detected by at least one E-node and (ii) when the sink sends a query to all E-nodes, the query affects the entire sensing field, i.e., the full coverage of a sensor network.

Let us consider the example WSN given in Fig. 2 (a) by having sensors with fully charged battery. Therefore, in this example the effective cost is based on the largest uncovered area in $\mathbf{A}$. In the initial step, all nodes are candidates and the coverage set $\mathbf{C}$ is empty. Then, in each iteration of Part II, the algorithm chooses the unselected node that has the minimum effective cost. In this example, sensor s_6 is selected in the first run of Part II and added to the set $\mathbf{C}$. Because it has the maximum uncovered sensing area and the minimum effective cost. In the second step, uncovered area is $\mathbf{A}/R_6$. According to this, we can see that s_7 is a redundant node after selecting s_6, having no uncovered sensing region. In the second run, effective cost of each unselected node is again calculated and this operation continues until $\mathbf{A}$ is fully covered.

Note that, residual energy of sensors changes over time. The energy consumption of E-nodes may be higher than the N-nodes. Thus, to balance the energy consumption, we trigger the classification process every $T_{\Delta U}$. In each round, current residual energy of sensors is used for calculating the cost. Thus, sensors whose residual energy is lower are less likely to become an E-node in the next update. Instead, N-nodes with higher energy levels may be replaced as essential. This is achieved by informing the sink about the estimated energy levels. Therefore, the sink keeps the energy level information up-to-date whenever a new message is received. Based on this information, when update process is triggered, a new essential set is constructed by running the same algorithm (Algorithm 1). Since the algorithm runs on the sink, it does not incur any overhead to sensor nodes. After each round, the sink informs sensors of their type by using a control message. In addition to energy conservation, our algorithm allows for selective redundancy in specific locations. For example, in the fire monitoring application, there may be several houses nearby an event incident site, thus the reports sent by the sensors that are closer to the houses are much critical than the others. In this case, sink may increase the redundancy in the area where sensors are located closer to the houses. This is achieved by activating the N-nodes in the critical area. The sink simply queries the E-nodes in the critical location to activate their neighboring N-nodes. Therefore, classification mechanism provides location-based redundancy when it is needed.

In the proposed mechanism, the connectivity is not considered because of two reasons. First, N-nodes are not put into

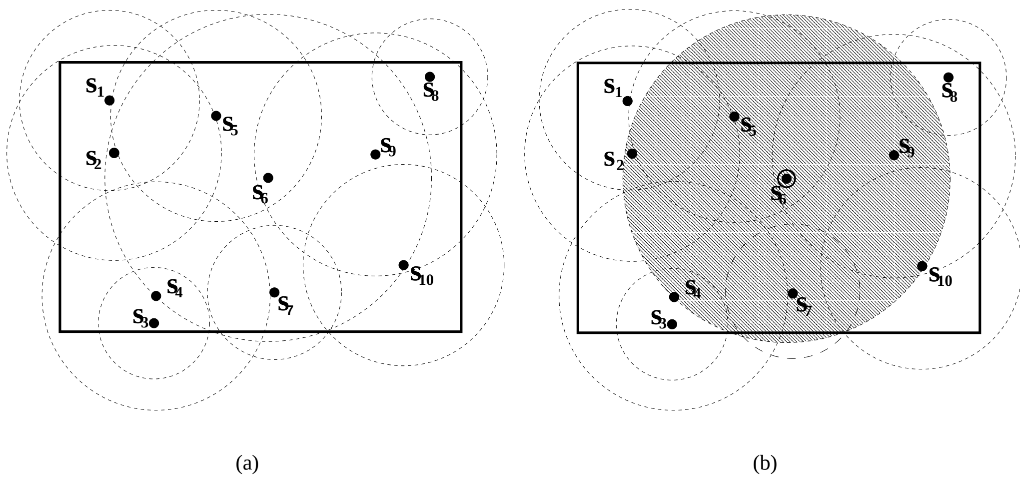

Fig. 2. Selecting Essential Nodes.

sleep mode may relay packets for enabling flexible use of routing protocols. Second, the network may be covered under the condition that is sufficient to the connectivity requirement [13]; thus, it is not necessary to take connectivity into account in the energy conservation algorithm. Next, we will analyze the complexity of the proposed algorithm and the energy consumption based on the definitions given in Section II.

IV. Complexity and Energy Consumption

In this section, we first present the analysis of computation complexity, which is critical to real-time and energy-limited sensor applications. Then, we discuss how energy is conserved with the proposed algorithm.

A. Complexity Analysis

Lemma 1: The cost of coverage set $\mathbf{C}$, is at most $O(ln(Nr^2))$ factor of the cost of the optimal solution, $\mathbf{C}^*$, where N is the number of sensor nodes and r is the sensing range.

Proof:

Let a be the unit area and I be the size of the sensing field in terms of unit a. Given N nodes which have minimum overlapping sensing regions, I is the size of the maximum fully covered sensing field. Our algorithm terminates when the sensing area is covered, thus in the worst case, the coverage area is I.

Algorithm attempts to minimize the overall cost, $Cost(\mathbf{C})$, which is also equal to the summation of the price of each unit area in the sensing field. That is,

$$\begin{aligned} Cost(\mathbf{C}) &= \textstyle\sum_{s_i \in \mathbf{C}} w(s_i), \\ &= \textstyle\sum_{j=1}^{I} price(a_j). \end{aligned}$$

where price of an uncovered unit area which will be covered by selecting sensor s_i can be written as:

$$price(a) = \{cost^{(c)}(s_i) | a \in R_i, s_i \in \mathbf{C}\}.$$

At the j^{th} iteration, the remaining uncovered area can be covered by the cost at most $\frac{OPT}{T-j+1}$, where OPT is the total cost of the optimal solution $\mathbf{C}^*$. Then we can write:

$$Cost(\mathbf{C}) \leq \textstyle\sum_{j=1}^{T} \frac{OPT}{T-j+1} = OPT.H_T$$

At the j^{th} iteration, the remaining uncovered area can be covered by the cost at most $\frac{OPT}{I-j+1}$, where OPT is the total cost of the optimal solution $\mathbf{C}^*$. Then we can write:

$$Cost(\mathbf{C}) \leq \textstyle\sum_{j=1}^{I} \frac{OPT}{I-j+1} = OPT.H_I$$

Since the H_T, harmonic number, is $O(lnI)$, Algorithm finds a coverage set at cost of at most $O(lnI)$ factor of the optimal cost.

Consider a network with a total number of N sensors with sensing range r. When the sensors are placed where the overlapping sensing areas are minimum, the maximum sensing field will be $\sqrt{27}Nr^2/2$ under the assumption of fully coverage [14]. Then, for the worst case (maximum sensing field with N nodes), we obtain that the upper bound is to be $O(ln(Nr^2))$ by replacing I with $\sqrt{27}Nr^2/2$.

■

Remark 1: Since the number of iterations in Part II is $O(N)$, the running time of Algorithm 1 is polynomial with upper bound $O(N^2)$.

B. Energy Consumption Analysis

Lemma 2: Given a set of sensors, total energy consumption per update interval is reduced proportional to the E-node ratio, g_k, when the classification mechanism is used.

Proof: In the proposed mechanism, N-nodes do not send/receive data from/to sink. Therefore, total energy consumption of an E-node, $p(t)^{(E)}$, and energy consumption of an N-node, $p(t)^{(N)}$ can be written as:

$$p(t)^{(E)} = p_r(t) + p_t(t) + p_f(t) \tag{7}$$

and

$$p(t)^{(N)} = p_f(t). \tag{8}$$

Then, average power consumption of an E-node is calculated by:

$$E\{p(t)^{(E)}\} = E\{p_t(t)\} + E\{p_r(t)\} + E\{p_f(t)\}. \tag{9}$$

We assume that transmitting, receiving and forwarding rates $r_r(t)$, $r_t(t)$ and $r_f(t)$, which are defined in (2) are uniformly distributed. Thus, average power consumption with uniformly distributed rates:

$$E\{p(t)^{(E)}\} = \mu_t \cdot E_b^t + \mu_r \cdot E_b^r + \mu'_f \cdot (E_b^t + E_b^r), \quad (10)$$

where μ_t, μ_r, and μ'_f are the average transmission rate, reception rate, and forwarding rate *after nodes classification*, respectively.

Similarly, average power consumption of an N-node is:

$$E\{p(t)^{(N)}\} = \mu'_f \cdot (E_b^t + E_b^r), \quad (11)$$

where μ'_f is the forwarding rate, when nodes are classified.

Let $g_k \in (0, 1]$ be the ratio of E-nodes during k^{th} update interval $T_{\Delta U}$ where $k = 1, 2, \ldots$. Since the data transmitted from/to sink are between E-nodes, sensor nodes forward at rate μ'_f which equals $\mu_f \cdot g_k$, where μ_f is forwarding rate *without node classification*, i.e., all nodes send and receive packets.

Then the total energy consumption in an update interval when classification is used, ε^C, is:

$$\begin{aligned} \varepsilon^C \;=\; & \sum_{i=0}^{N \cdot g_k} T_{\Delta U} \cdot E\{p(t)\}^E \quad (12) \\ & + \sum_{i=N \cdot g_k}^{N} T_{\Delta U} \cdot E\{p(t)\}^N. \end{aligned}$$

When there is no classification, all nodes act as E-nodes, thus total energy consumption is:

$$\varepsilon = \textstyle\sum_{i=0}^{N} T_{\Delta U} \cdot E\{p(t)^{(E)}\}. \quad (13)$$

Then the fraction of energy consumption using classification to no-classification is:

$$\frac{\varepsilon^C}{\varepsilon} = \frac{g_k \cdot (E_b^t \cdot \mu_t + E_b^r \cdot \mu_r + (E_b^t + E_b^r) \cdot \mu_f)}{E_b^t \cdot \mu_t + E_b^r \cdot \mu_r + g_k \cdot (E_b^t + E_b^r) \cdot \mu_f}. \quad (14)$$

■

Therefore, the total energy consumption within an update interval, ε^C, is proportional to the E-node ratio because $g_k \leq 1$; then it is less than or equal to the total energy consumption, ε, without classification. The equality occurs at the worst time that all of the nodes in the sensing field are essential nodes, which means the network is covered by the minimum number of sensors without any redundancy.

V. Simulation

A. Simulation Environment

The performance of the classification algorithm is evaluated using ns2 simulator [9]. Simulations are performed for a 500 m x 500 m square area consisting of different numbers of sensor nodes, distributed randomly over the sensing field such that sensing field is fully covered.

In our experiments, we use a mobile tracking application in which the movements of a mobile node are reported to the sink in every sensing period. Movements of the mobile (phenomenon) node are generated with *random waypoint* model. *Event-driven* data delivery model is used from sensors to the sink, where sensors send an event report if the phenomenon is in their sensing region. The coordinates of the sink remains the same during the experiments which is randomly determined.

TABLE II

Simulation Parameters

Area of sensing field	500x500 m^2
Number of sensor nodes	150
Radio range of a sensor node	100 m
Sensing range of a sensor node	100 m
Packet length	100 byte
Transmit power	175 mW
Receive power	175 mW
Routing protocol	AODV
MAC protocol	CSMA/CA

B. Simulation Results

The simulation experiments are designed to show the energy consumption of nodes in time, number of packets injected to the network and number of alive nodes in time.

First, we investigate the robustness of the proposed algorithm in terms of the ratio of essential nodes in a sensing field. In Fig. 3, E-node ratio is depicted for different node densities. Note that, given the fixed area of sensing field, the node density depends on the number of nodes. Among the three, the network having 250 nodes has the lowest ratio of E-nodes, thus showing that the greedy algorithm performs even better in densely deployed networks. Also results in Fig. 3 indicate that the ratio of E-nodes does not vary in time. In every 2 sec, our algorithm finds a new set of E-nodes which performs well in networks with different node densities.

In Fig. 4, we show the average residual energy of sensors in time. For example at time t=6 sec, the residual energy of sensors is up to 60% when classification algorithm is used compared to 48% residual energy where classification has not been used. According to the Fig. 3, E-node ratio of this scenario is around 40%, which is the dominant factor of reducing energy consumption.

We also show how the data traffic is reduced in Figure 5. Compared to no-classification, the total number of messages

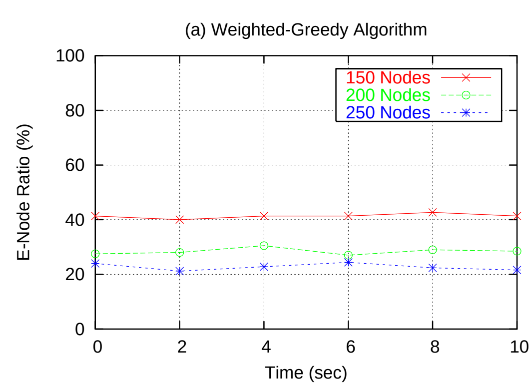

Fig. 3. E-Nodes Ratio.

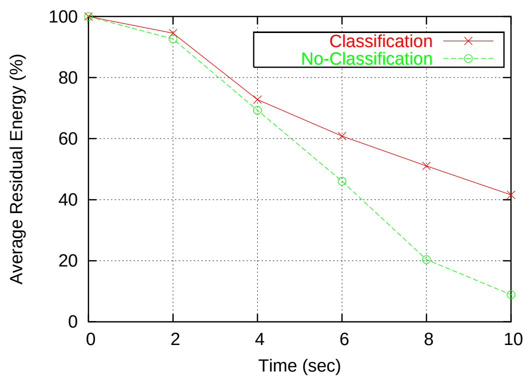

Fig. 4. Residual Energy.

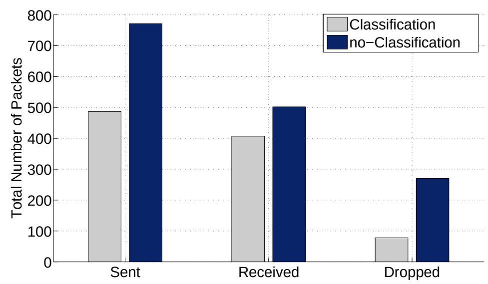

Fig. 5. Transmitted, received and dropped packets.

sent are significantly decreased when proposed algorithm is used. The reason is that, N-nodes do not send any new message, which decrease the number of sent, received and dropped packets.

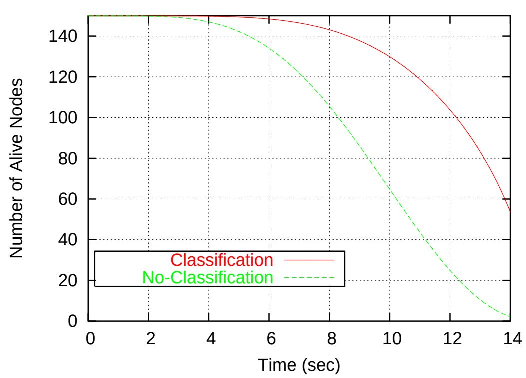

Fig. 6. Number of Alive Nodes.

Finally, we show the effect of energy conservation over the network lifetime. For the same scenario, we show the number of alive nodes with the initial energy of 1 J in Fig. 6. According to Fig. 6, number of alive nodes is much larger due to energy conservation. In fact, the rotation of the E-nodes, which balances the energy consumption among sensors, is also effective in prolonging the lifetime.

VI. Conclusion

In this paper, we have proposed a weighted-greedy algorithm that classifies sensors based upon their residual energy. Essential nodes, selected by our classification algorithm, cover the sensing field. Therefore, we guarantee that an event can be detected by at least one E-node. Also whenever the sink sends a query to all E-nodes, this query affects the entire sensing field. Proposed algorithm makes use of lightweight classification which decreases the number of data packets sent to the sink, conserving transmission/reception energy consumption of non-essential nodes. Moreover, we balance the energy consumption among nodes by dynamic rotation which may highly affect the network lifetime.

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