Distributed energy balanced routing for wireless sensor networks

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ABSTRACT
Most routing algorithms for sensor networks focus on finding energy efficient paths to prolong the lifetime of sensor networks. As a result, the power of sensors on efficient paths depletes quickly, and consequently sensor networks become incapable of monitoring events from some parts of their target areas. In many sensor network applications, the events that must be tracked occur at random locations and have non-deterministic generation patterns. Therefore, ideally, routing algorithms should consider not only energy efficiency, but also the amount of energy remaining in each sensor, thus avoiding non-functioning sensors due to early power depletion. This paper introduces a new metric, energy cost, devised to consider a balance of sensors’ remaining energies, as well as energy efficiency. This metric gives rise to the design of the distributed energy balanced routing (DEBR) algorithm devised to balance the data traffic of sensor networks in a decentralized manner and consequently prolong the lifetime of the networks. DEBR is scalable in the number of sensors and also robust to the variations in the dynamics of event generation. We demonstrate the effectiveness of the proposed algorithm by comparing three existing routing algorithms: direct communication approach, minimum transmission energy, and self-organized routing and find that energy balance should be considered to extend lifetime of sensor network and increase robustness of sensor network for diverse event generation patterns.

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1. Introduction

As a result of the advances in wireless communication and electronics technologies, wireless sensors are getting smaller, cheaper, and more powerful. The development of these miniaturized wireless sensors enables to use sensor networks for many applications such as military surveillance, environmental monitoring, infrastructure and facility diagnosis, and other commercial applications (Akyildiz, Su, Sankarasubramaniam, & Cayirci, 2002; Jeong & Nof, 2008; Ok et al., 2007). A fundamental objective of the wireless sensor networks is to report events of a predetermined nature or transmit sensed data to sink nodes or the base station for further analysis (Estrin, Govindan, Heidemann, & Kumar, 1999; Akyildiz et al., 2002; Tubaishat & Madria, 2003). To achieve this objective, a proper routing algorithm that determines the paths of the data flow should be present. While considering this basic requirement, the design of the routing algorithm should also incorporate the following factors:

- Due to sensors’ limited power, the routing algorithm should have a design to allow finding paths consuming the least amount of power to prolong the lifetime of the sensor network.
- However, inevitably, most energy efficient routing algorithms route significant traffic via some sensors, which are close to the base station or on energy efficient paths and thereby, drain their power quickly. As a result, the sensor networks become unable to detect events from regions where all sensors are non-functioning. Thus, in sensor networks, apart from energy efficiency, the distribution of the data traffic over the whole network is an important factor towards extending its lifetime.
- Although most existing routing algorithms assume that events are generated uniformly at each sensor, events could occur randomly (Braginsky & Estin, 2002), uniformly (Rogers, David, & Jennings, 2005) over the target area, or repeatedly (Butler & Rus, 2003) at a specific part of the target area. Even, event patterns can change from one type to another over time. Therefore, the routing algorithm should be sufficiently robust for diverse event generation functions. Addressing this problem by planned routing utilizes the energy uniformly over the entire sensor network.
- A sensor network can consist of a large number of nodes for which a central control architecture does not apply. Therefore, the routing algorithm should adopt a local decision making scheme.

Although the literature includes several routing algorithms, such as direct communication approach, hierarchical routing methods (Heinzelman, Chandrakasan, & Balakrishnan, 2000;
Lindsey, Raghavendra, & Sivalingam, 2002), self-organized routing algorithm (Rogers et al., 2005), and other routing algorithms (Chang & Tassiulas, 2004), little evidence exists for the effectiveness and efficiency of these algorithms with respect to the considerations mentioned earlier.

The primary idea of this research is that sensor networks can respond properly to events that have uncertainty in their position and generation rates and maximize the period when they function fully through energy balancing. In Fig. 1, a sensor network has three sensors and the sensors send their messages to the base station sequentially and repeatedly. Each sensor has 9 units of an initial energy and the numbers above arrows indicate the amounts of energy required to the corresponding transmissions. If all sensors use only energy efficient paths, sensor 1 becomes depleted after each sensor transmits its message to the base station three times (Fig. 1a). Since the events have uncertainties in their positions and generation rates, this sensor network might not respond properly to upcoming events after a period of time during which sensors become inactive from energy depletion. However, an energy balanced sensor network with alternative paths remains event-ready after a similar period because all sensors remain active (Fig. 1b). To capture the advantages of energy balance, this study proposes a new heuristic metric, called energy cost (EC), to establish energy efficiency as well as efficiency. Since the EC is transmission energy cost relative to available energy, its value is low when required energy for transmission is low and available energy is high. Using this characteristic of this metric, a localized routing algorithm, the distributed energy balanced routing (DEBR), is proposed to accomplish energy balance of sensor networks in an energy efficient manner.

The organization of the rest of the paper is as follows. Section 2 details the sensor networks under consideration and Section 3 summarizes related work. Section 4 contains an explanation of a mathematical model for energy balanced routing problem. After describing the details of the distributed energy balanced routing (DEBR) algorithms in Section 5, in Section 6 we present extensive simulation results, and conclude in Section 7.

2. Sensor network model

With n homogenous sensors randomly and uniformly distributed over a target area, all sensed data must be sent to the base station. The sensors are limited in power. Sensors can control their respective transmission power for minimal consumption to transmit to a destination (Heinzelman et al., 2000; Lindsey et al., 2002; Ramanathan & Rosales-Hain, 2000; Wagner & Cristescu, 2005; Wattenhofer, Li, Bahl, & Wang, 2001; Zhang & Hou, 2005). This is the minimum requirement for allowing the routing algorithm to maximize sensor networks’ operational times. The details of the sensor network model we consider are:

2.1. Network topology

Each sensor uses a fixed transmission power for communicating with its neighboring sensors; whereas, it transmits data to the base station with the minimum transmission power. The neighboring distance is the maximal reachable distance with the fixed transmission power for neighboring sensors. For a given sensor the sensors within its neighboring distance are its “neighboring sensors” or “neighbors.” In this scheme, each sensor can be aware of the current energy level of its neighbors or energy required to transmit from its neighboring sensors to the base station by anticipating and/or eavesdropping for data from the neighbors (IEEE.802.11., 1999). A sensor’s neighboring sensors can receive all the messages the sensor transmits, since every node has the same neighbor distance. When a sensor transmits a message to one of its neighboring nodes or the base station, the sensor adds its available energy after transmission to the data so that all of its neighbors can update its energy level. This updating process guarantees that information of neighboring sensors for the routing decision is available for sensors. On the other hand, one of the typical methods to save energy in sensor networks is to consider a duty-cycle based on sensors in the design of the medium access control (MAC) layer (Bennett et al., 1997; IEEE.802.11., 1999; Tseng, Hsu, & Hsieh, 2002; Wang & Yang, 2007; Ye, Heidemann, & Estin, 2004). Although sensors turn their radio off during idle period to save their energies, these MAC schemes guarantee that the awake/sleep schedules of all sensors or, at least, neighboring nodes are synchronized. Therefore, sensors can be aware of the current energy levels of its neighboring nodes regardless of the design of the MAC layer.

Many applications (Heinzelman et al., 2000; Lindsey et al., 2002; Rogers et al., 2005) assume that all sensors have an ability to communicate with the base station directly as shown in Fig. 2a. In some other applications (Intanagonwiwat, Govindan, & Estrin, 2000; Olariu & Stojmenović, 2006), only a small portion of sensors can communicate with the base station directly due to their limited transmission capabilities. In Fig. 2b, the sensors located in area A can only transmit data to the base station directly. In this scenario, the sensors in area A use the power in their batteries more quickly than the other sensors, because they need to transmit the other sensors’ data as well as their own data. Since no way exists to transmit data to the base station when all sensors in A expend their energies completely, the energies of the sensors in A should be more efficiently and effectively used. In other words, the data transmission capacity of area A determines the lifetime of the overall sensor network (Olariu & Stojmenović, 2006). In fact, the area A in Fig. 2b can be considered as a different network on its own. In this work, we consider the sensor networks in which all sensors can communicate with the base station directly.

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1 Generally, a battery power is measured in Joule (J). To simplify the explanation, we just remove the specific power unit.
2.2. Energy consumption model

Each sensor uses a fixed transmission power for communicating with its neighboring sensors while each sensor transmits data to the base station. The neighboring distance is defined as the maximal reachable distance with the fixed transmission power for neighboring sensors. For a given sensor the distances within its neighboring distance are its “neighboring sensors” or “neighbors”. This scheme reduces the operational complexity because it does not require sensors to be aware of the positions of their neighbors as long as the neighbors are within the neighbor distance. Also, each node can be aware of the current energy level of its neighbors or energy required to transmit from its neighboring nodes to the base station by anticipating and/or eavesdropping data from the neighbors.

Generally, sensors consume energy when they sense, receive and transmit data (Wang & Yang, 2007 #68). However, the amount of energy consumption for sensing is unaffected by the routing algorithm and only a small difference exists between the power consumption for idle and receiving modes (Stemm & Katz, 1997). Therefore, in this work, we consider only the energy consumed while transmitting messages. According to the radio model (Heinzelman et al., 2000), energy consumption \( E \) for transmitting data is proportional to the transmission distance as well as the square of the amount of data. By normalization of the amount of sensed data, the energy consumption model is simplified to \( E = d^2 \), where \( E \) and \( d \) are the required energy and the transmission distance, respectively (Rogers et al., 2005).

2.3. Lifetime of sensor network

We validate the effectiveness of the proposed DEBR routing algorithm using a sensor network’s lifetime as the performance measure. The definition of sensor network lifetime is the time until the first node or a portion of nodes become incapable, due to energy depletion, of sending data to its neighbors (Chang & Tassiulas, 2004; Gandham, Dawande, Prakash, & Venkatesan, 2003; Lindsey et al., 2002; Rogers et al., 2005; Zhang & Hou, 2005). The portion (number of depleted nodes) can vary depending on the context of the sensor networks. In this paper, the lifetime of a sensor network is the number of rounds until the first (\( L_1 \)), 10% (\( L_{10} \)), or 20% (\( L_{20} \)) of node(s) expend all their energy (Chang & Tassiulas, 2004; Zhang & Hou, 2005). We say that \( L_1 \) denotes the full functioning period of the sensor network.

2.4. Event generation functions

Many previous studies of routing algorithms assumed that all sensors have uniform data or event generation rates (Heinzelman et al., 2000; Lindsey et al., 2002; Rogers et al., 2005). In infrastructure monitoring applications, each sensor performs a sensing task for every fixed time and has a homogeneous event generation function or the same event generation rate. However, in many sensor network applications, this assumption becomes unrealistic. In a monitoring the migration of a herd of animals, the animals might move along a path in the target area repeatedly (Butler & Rus, 2003). In the case of forest fire detection, events occur rarely and randomly over the target area (Braginsky & Estin, 2002). Therefore, to evaluate the robustness of routing algorithm the consideration of diverse potential event generation patterns is more reasonable. For our work, three event generation functions are considered as follow:

- **Uniform** event generation: Every sensor has a data packet to be reported in a fixed time or round.
- **Random** event generation with random rate \( \alpha \): Every sensor has a data packet to be reported with probability \( \alpha \) in a fixed time or round. The probability \( \alpha \) is called random rate.
- **Repeated** event generation from a local area \( A \): Only the sensors in a local area \( A \) have data packets to be reported in a fixed time or round. The shape of the area can be a point, a circle, a square, or any other.

3. Routing in wireless sensor networks

Significant efforts have attempted to develop routing algorithms to extend the lifetime of sensor networks. Hierarchical routing considers data aggregation and fusion in order to reduce the number of transmissions to the base station (Heinzelman et al., 2000; Lindsey et al., 2002; Manjeshwar & Agrawal, 2001; Matrouk & Landfeldt, 2009; Younis & Fahmy, 2004). Through clustering and cluster header selection rules, these hierarchical approaches spread energy usages over the whole network to extend the operational time of sensor networks. Heinzelman et al. (2000) proposed low-energy adaptive clustering hierarchy (LEACH), a clustering-based protocol that utilizes a randomized rotation of local cluster-heads to evenly distribute the energy load among the sensors.
in the network. In LEACH, to enhance system lifetime, each sensor has data fusion capability to reduce the amount of data to the base station. RETT-gen (Matrouk & Landfeldt, 2009) modifies LEACH by considering sensors’ residual energies directly on routing decisions of sensors. Dissipating data traffic or energy load evenly all sensors in sensor networks, RETT-gen extends the lifetime of the sensor networks. In the both hierarchical routing algorithms, forming clusters and the randomized rotation of cluster-heads incur high overhead and complexity.

Power-efficient gathering in sensor information systems (PEGA-SIS) (Lindsey et al., 2002) introduces a new metric, energy-delay which simultaneously minimizes energy and delays cost for data gathering from sensor networks. In this routing scheme, all sensors form a chain and communicate with the base station through a leader sensor which is selected randomly for each round. Also, this routing algorithm uses data fusion to reduce the amount of data to be transmitted. However, one requirement is that sensors have the global information about the whole network and apply a greedy algorithm to build the chain.

Hybrid, energy efficient, distributed clustering approach (HEED) (Younis & Fahmy, 2004) balances energy usage of sensors and improves network scalability and lifetime by topology control. In every clustering period, sensors become a cluster-head with a probability proportional to its residual energy. To prevent sensors from having more than one cluster-head, this algorithm introduces an inter-cluster communication energy cost, and sensors choose a cluster-head to minimize the energy cost. However, to balance residual energies of sensors, HEED requires frequent re-clustering causing a high, overhead cost, synchronization problem among sensors.

Threshold sensitive energy efficient sensor network protocol (TEEN) (Manjeshwar & Agrawal, 2001) was devised for reactive networks which have sudden and drastic changes in the sensed attributes. Based on a hierarchical grouping where closer nodes form clusters, sensors send the sensed data to their cluster-head when this sensed value reaches a threshold value. The main drawback of TEEN is the necessity for high overhead and complexity involved with forming clusters at multiple levels. Even though these hierarchical routings produce good results in some applications with high redundancy in their data, no evidence exists that the algorithm works well with the applications in which all sensed data should be sent to the base station.

Chang and Tassiulas (2004) proposed a shortest cost path routing algorithm called the flow augmentation (FA) algorithm. This algorithm chooses a path which consumes less energy and does not include a node with small residual energy for a given data packet. Applying this heuristic rule to each data, the FA algorithm finds the shortest cost path and achieves a balance of residual energy over the entire network. This algorithm assumes that sensors have global information about the topology of networks to find the sufficient energy path. In spite of the superiority of this algorithm with diverse configurations of sensor networks, this algorithm is not adequate for large size networks and is not adaptive to dynamic network environments.

To extend the lifetime of sensor networks in which all sensed data should be reported in its original form, Rogers et al. (2005) proposed a self-organized routing (SOR) algorithm. In this algorithm, a sensor saves its energy by hiring another sensor as a mediator. To make sensors act willingly as mediators, Rogers et al. introduce a delicate payment scheme. Sensors earn different payments depending on whether they transmit their own data or mediate other sensors’ data. If a sensor can get more payment, it is willing to be a mediator for other nodes. This algorithm has several desirable properties. Energy-efficiency and energy balancing are pursued together through the selfish behaviors, sensors make local decisions based on local information, and there is no limitation to the solution space. Therefore, in the result section, we compared the SOR algorithm with our algorithm directly.

4. Integer programming (IP) model for energy balanced routing

In this section, we formulate an energy balanced routing problem as an IP problem. Consider a sensor network where n sensors are deployed randomly and uniformly in a target area, and the sensors transmit all sensed data to the base station. N and B denote the set of sensor nodes and the base station. Sensor i, i ∈ N has a set of neighbor nodes (Ni) according to the network topology. Ei and Di(T) are the battery capacity of sensor i and the data traffic generated by sensor i during any time interval [0, T]. Lastly, ei and xi represent the required energy for a transmission and the number of transmissions from node i to Ni, respectively. Given a time interval [0, T] and Di(T), i ∈ N, the IP problem involves maximizing the minimum residual energy of sensors at time T.

4.1. Traffic equations

Since all sensed data should be sent to the base station, the incoming and outgoing data traffic at a sensor are the same. The incoming traffic at node i consists of data from its neighbors and data generated by node i itself during the time interval [0, T]. On the other hand, the outgoing traffic is the sum of the traffic sent by a sensor i to neighbors of the sensor and the base station. Therefore, the traffic equation for each node is:

\[ \sum_{j \in N_i} x_{ji} + D_i(T) = \sum_{j \in N_i \cup \{B\}} x_{ij} \quad \text{for all } i \in N \]  

In fact, constraints (1) guarantee that all data are transmitted to the base station. By summing (1) for i the following equation can be obtained:

\[ \sum_{j \in N} x_{jB} = \sum_{i \in N} D_i(T) \]  

The incoming traffic to the base station is equal to data generated by all sensors during [0, T].

4.2. Energy constraints

The residual energy of sensor i at time T is the initial energy of sensor i minus the total energy consumed to transmit data to neighbors and the base station. Eq. (3) guarantees that the residual energies of all sensors are greater than and equal to the minimum residual energy of sensors, R.

\[ E_i - \sum_{j \in N_i \cup \{B\}} e_{ij} x_{ij} \geq R \quad \text{for all } i \in N \]  

4.3. Integer programming (IP) formulation

Now, we have an IP formulation maximizing the minimum residual energy of sensors. The objective is to maximize the minimum residual energy of sensors, R, with the constraints of Eqs. (1)–(3) is:

Maximize \[ R \]

s.t. \[ \sum_{j \in N_i} x_{ji} + D_i(T) = \sum_{j \in N_i \cup \{B\}} x_{ij} \quad \text{for all } i \in N \]

\[ E_i - \sum_{j \in N_i \cup \{B\}} e_{ij} x_{ij} \geq R \quad \text{for all } i \in N \]  

\[ X_{ij} : \text{non-negative integer for all } i \text{ and } j. \]
The result of this problem provides routing policies \((x_i)\) for sensor nodes so that make the given sensor network energy balanced at time \(T\). While, this IP problem can be transferred to another IP model (Chang & Tassiulas, 2004) maximizing the lifetime of sensor networks by setting \(R = 0\) and replacing the objective function in (4) by “Maximize \(T\). For computational convenience we solve the IP problem as LP problems to derive the upper bound for the performance of routing algorithms. A transformation to LP requires the assumption that \(D(T)\) is a linear function of \(T\).

5. Distributed energy balanced routing (DEBR)

The proposed routing algorithm uses a path with energy sufficiency as well as energy efficiency to pursue energy balance for the sensor network. Energy sufficiency depends upon the available energy, and energy efficiency depends upon the required energy. By using a composite of both quantities, a good path that achieves energy balance can be found. Only one of them, by itself cannot indicate the goodness of a path because of the dual objectives of not depleting the energy reserves of popular paths and of sending messages through energy efficient paths to ensure the total energy needed to route the messages are kept to a minimum. The definition of the composite measure, energy cost \((EC)\) for a transmission from node \(i\) to \(j\) is:

\[
EC_{ij} = \frac{\text{Required energy from node } i \text{ to } j}{\text{Available energy at node } i}
\] (5)

The basic idea of the proposed routing algorithm is to use a path having the minimum \(EC\). When a sensor \(i\) sends data to the base station, it can transmit data to the base station directly or route the data to one of its neighbors \((N_i)\). In other words, the sensor determines which sensor is the best candidate for direct communication with the base station among its neighbors and itself. For evaluating these alternatives, sensor \(i\) considers the total required energies to the base station via neighboring nodes. The total energy cost \((TEC_{ik})\) of a neighboring node \(k\) at sensor \(i\) is simply the sum of the energy costs from node \(i\) to \(k\) and from node \(k\) to the base station:

\[
TEC_{ik} = EC_{ik} + EC_{kB}
\] (6)

This measure is the composite quantity that indicates the goodness of a path including a neighboring node. Based on this metric, sensor \(i\) can select the best candidate, node \(K\), for direct communication with the base station:

\[
K = \text{Argmin}_{j \in N_i} (TEC_{ij}).
\] (7)

If the best candidate node is the node \(i\) itself, it sends data to the base station and completes the routing process for the data. Otherwise, it forwards the data to the best candidate among its neighboring nodes and that node then repeats the same routing process. This process continues until a node selects itself as the best candidate and sends directly to the base station. This localized decision making process results in a monotonic decrease of energy cost over time because the best candidate can have an indirect path that is better than direct transmission. Each sensor makes its decision with the assumption that one of its neighboring nodes sends data to the base station directly. Sensors do not care if the receiving node sends data to the base station or passes data to one of its neighboring nodes. Through this local decision making process, a sensor network can achieve energy balance and prolong the lifetime of the sensor network.

We show an example of the running of the DEBR algorithm, and then discuss the details and the characteristics of the proposed algorithm.

5.1. Example

In Fig. 3, node \(n_1\) has three alternative routes to the base station, which are two indirect routes via neighboring nodes and one direct route. \(EC_{e_i}\) represents the currently available energy of node \(i\) and the required energy for transmission from node \(i\) to \(j\), respectively. The node \(n_1\) calculates \(TEC\) value for each alternative route as in Fig. 3c. The second column shows the energy cost for direct transmission to the base station from an alternative node, and the third column for the transmission to a neighboring node. The energy cost to each neighbor is the same because the transmission power for neighbors is fixed. By totaling these two columns, the total energy cost for each route is shown in the last column. The computational results indicate that route 3 is the least energy-expensive one with \(TEC_3 = 0.24\). However, this cost can further decrease if the node \(n_2\) has more cost-effective routes than direct transmission. Node \(n_1\) chooses \(n_3\) as the best candidate and sends data to \(n_3\). At this moment, the node adds its available energy, after transmission and destination, to the data so that all of its neighbors can update their EC tables accordingly. A node needs only the information of its neighbors for the routing decision and this updating process guarantees it since every node has the same transmission power for its neighbors. After receiving this data from node \(n_1\), node \(n_3\) starts a routing process again. This routing process continues until the base station receives the data.

5.2. Steps in the DEBR algorithm

Each sensor keeps a small EC table. The EC table contains node identification number, minimum transmission power to the base station, and available energy for each neighboring node. The steps of the algorithm are:

A. Initialize EC table: During the setup period, each sensor finds its minimum transmission power to the base station. Then, each sensor broadcasts a setup message to neighboring nodes using a pre-set transmission power. This setup message includes node identifier, minimum transmission power to the base station, and available energy. Every node receiving this broadcast message registers the transmitting node as one of its neighbors. Since all nodes have an identical neighbor distance, two nodes within the neighbor distance are neighbors to each other. After the setup period, all sensors initialize their EC tables.

B. Update EC table: The routing table reflects changes of neighbors’ energy levels. When a sensor transmits data, all of its neighbors receive this data and get the current battery level of the transmitting sensor. As a result, whenever a sensor’s battery level changes, all routing tables, including the corresponding sensor information, are updated.

C. Decentralized routing decision: Based on their EC table, all nodes make a local routing decision. Based on (7), node \(i\) selects \(K\) as the best candidate for transmitting data to the base station without considering whether \(K\) sends data directly to the base station or not. For tie breaking, if a direct path and an indirect path result in the same \(EC\), the direct path is selected to reduce the number of transmissions or hops. In the case of two indirect paths having the same \(EC\) values, any path of them can be selected.

Fig. 4 shows how the DEBR algorithm operates over a sensor network. For a given data, \(n_i\) chooses \(n_j\) among several possible routes. After the data passes to \(n_k\) energy level of \(n_i\) changes and the EC table of \(n_i\) also changes. \(n_i\) performs the same process sequentially. In the figure, \(n_i\) sends data to the base station directly.
because \( n_3 \) itself, has the minimum energy cost compared to other indirect routes.

5.3. Algorithm characteristics

This section discusses the characteristics of the DEBR algorithm.

5.3.1. Observation 1

DEBR occasionally prevents sensors from using the most energy efficient path to achieve an energy balance of sensors. As described in Fig. 5, even though \( e_{BS} < e_{2BS} + e_{12} \), sensor 1 sends data to sensor 2 instead of to the base station directly because \( E_1 > E_2 \). As a result, sensor 1 having relatively low-energy can conserve its energy by passing the data to sensor 2 with relatively higher energy. Through this characteristic DEBR can achieve an energy balance over the entire network.

5.3.2. Observation 2

DEBR guarantees elimination of loops in any routing path. After sensor A sends data to sensor B located on the minimal energy cost path, sensor B also considers sensor A as one of the candidates for data transmission. However, sensor B never routes data to sensor A, because the energy cost of using sensor A is greater than that of direct transmission from sensor B to the base station. In DEBR, a sensor routes data to a neighbor only if the neighbor incurs less energy cost than the sensor itself. As this routing mechanism continues, the energy cost of the original node is apparently greater than that of the next down-stream node. Therefore, DEBR always assures finding a routing path to the base station without loops.

5.3.3. Observation 3

The performance of the proposed algorithm heavily depends on the neighboring distance. As the neighboring distance increases, the number of neighbors also increases and each sensor has a better chance to find less costly energy paths. However, an increase in neighboring distance also implies an increase in energy required to reach neighboring nodes. Therefore, an optimally desirable neighbor distance exists that balances these two competing criteria. This distance also depends upon the density of sensors.

6. Experimental results

In this section, we provide several experimental results to validate the effectiveness of the DEBR algorithm. The comparison of the algorithm is with three other algorithms discussed in (Heinzelman et al., 2000; Rogers et al., 2005): direct communication (DC), minimum transmission energy (MTE), and self-organized routing (SOR). In DC, every sensor simply transmits data directly to the base station without considering any energy efficient indirect path. MTE and SOR consider indirect routing to save sensor power but make routing decisions based on energy efficiency only. We coded the four routing algorithms in C programming language while solving the mathematical model using a commercially available LP solver (LINDO, 1996).

Two different shapes of sensor networks are used (see Fig. 6). Previous research has used these two shapes with adjusting scales (Lindsey, Raghavendra et al., 2002; Rogers, David et al., 2005). The first example is a sensor network with 100 nodes randomly uniformly deployed in a 100 m \( \times \) 100 m square area with the base station located at (50,150). The other example has 100 sensors randomly deployed in a 100 m-radius with the base station at (0,0). In the square and circle sensor networks one sensor has an assigned initial battery level of 250,000 and 100,000, respectively. The initial energy levels are established by determining the
amount of energy needed for the farthest node to transmit data to the base station 100 times with DC (Rogers et al., 2005). Because the sensor networks are randomly generated, 100 repeated experiments for each condition provides an average for the results.

The empirical analysis consists of three parts. First, we compare the lifetime of DC, MTE, SOR, and DEBR. The second part provides the effects of neighbor distance on the proposed algorithm. Finally, the third part demonstrates how the DEBR algorithm is robust for diverse event generation patterns.

6.1. Lifetime of sensor network

This experimentation evaluates the performance of the DEBR algorithm with 20 m neighboring distance of the square sensor network. Fig. 7a plots the number of active sensors against the number of rounds for each algorithm. We call it a round that every sensor sends its data to the base station once. This graph shows that DEBR-20 m has better performance than DC, MTE, and SOR algorithms until 50 (%) of nodes die. Also noticeable is that the DEBR algorithm has similar patterns to the optimal. Sensors in DC, MTE, and SOR algorithms depleted their energies gradually with time. However, in the DEBR algorithm, the majority of sensors is alive up to 200 rounds and deplete simultaneously, thus indicating good energy balancing throughout the network. Similarly, Fig. 7b provides the performance result for the four routing algorithms with the 100 m radius sensor network. Although the superiority of performance is reduced, still, DEBR shows better performance than the other three algorithms until 40 (%) of nodes drain. Also Fig. 7a and b show the lifetimes of the sensor networks (L₁, L₁₀, L₂₀) according to the definitions in Section 2. DEBR-20 m is dominantly better than the three other routing algorithms for all various lifetime definitions, with 2.5, 2, and 1.7 times for DC, 20, 5, and 2.5 times for MTE, and 10, 2, and 1.5 times for SOR.

Similar observations can be found even for random and repeated event generation patterns as shown in Fig. 8a and b, respectively. Especially, the performance of DEBR in repeated generation is dominantly better than others in all different definitions of the lifetime. With these findings, we can conclude that our algorithm is superior to other routing algorithms regardless of event generation patterns, thus robust.

6.2. Energy balancing

Fig. 9 shows how well DEBR achieves the energy balance of sensors over the network. As discussed in Heinzelman et al. (2000), in DC (Fig. 9a), MTE (Fig. 9b) and SOR (Fig. 9c) schemes, sensors far away and close to the base station depleted their energies about round 150. While, in DEBR, all sensors remain live and even have sufficient energy for responding to upcoming events (Fig. 9d). Also notable is that DC, MTE, and SOR missed some events during the first 150 rounds. However, DEBR guaranteed that all data was transmitted to the base station for the same period.

Fig. 10 shows the result of the IP problem in Section 4 and the residual energy distribution of sensors according to their y-axis distance in DEBR. In the case of IP, all sensors have the same residual energy, 1.2 × 10⁶, after 150 rounds. On the other hand, in our
algorithm, the residual energy of sensor increases as the distance to the base station does. This is due to that DEBR pursues an energy balance over sensor network in terms of direct communication capacity instead of the amount of energy. This is a desirable property of our routing algorithm because all sensors are guaranteed to have the same capability to deliver their data to the base station with time.

Fig. 11 shows the routing paths for four algorithms with repeated events in the regions from (0,0) to (50,50). In the case of DC, MTE, and SOR, data traffic concentrates in specific sensors which have location in the region or on the efficient path. On the other hand, DEBR tries to disperse energy usage over the whole network to achieve energy balance. As a result, DEBR can keep all sensors operating for as long as possible.

6.3. Different event generation functions

To identify the effect of different event generation types on the lifetime of a sensor network, performed simulations use uniform, random, and repeat event generation functions. In the case of the random distribution, 25% of sensors have events randomly occurring in each round. While, for the repeat events, the assumption is that sensors from (0,0) to (50,50) observe repeated events.

Table 1 gives the results of the lifetime of sensor networks \(L_{1}, L_{10}, L_{20}\) for DC, MTE, SOR, and DEBR algorithms with three different event generation types. As shown in Table 1, DEBR shows a dominant performance compared with DC, MTE and SOR over the time. Especially, in the case of \(L_{1}\), DEBR gives approximately two to eight times better performance than the others.
Fig. 10. Remaining energy distributions of sensors with their distances to the base station at (50, 150) with uniform events for DEBR after 150 rounds.

Fig. 11. Routing paths by DC, MTE, SOR, and DEBR with repeat events on the region from (0, 0) to (50, 50).
6.4. Neighbor distance

Fig. 12 shows the effects of neighbor distance on the lifetime of the square sensor network. The results show that the performance of the DEBR algorithm depends on neighbor distance or equivalently the number of neighbor nodes. Fig. 12a shows that the increase in neighbor distances results in an increase in the number of neighbor nodes. However, Fig. 12b shows that such an increase does not lead to a monotonic increase of the lifetime. This phenomenon is due to the following two reasons; (1) the increased distance requires more transmission power between neighbors and (2) sensors have to expend the same transmission power for its neighboring nodes regardless of the actual distances to neighboring nodes. In this experiment, the best neighboring distance for the DEBR algorithm is 22 m, 17 m, and 16 m (ranging between 8 and 12 neighbors) for \( L_1 \), \( L_{10} \), and \( L_{20} \).

7. Conclusion and future works

Sensor networks should be able to achieve energy balance as well as energy efficiency to prolong their lifetimes and prepare for the uncertainties of event generation. Most energy aware routing algorithms are only concerned about energy efficiency. This paper presents a heuristic criterion, called energy cost, to consider energy balance and efficiency simultaneously. Using this metric, we have designed and implemented the distributed energy balanced routing (DEBR) algorithm.

The designed algorithm demonstrates its superiority to direct communication (DC), minimum transmission energy (MTE), and self-organized routing (SOR) with a lifetime metric, generally accepted for evaluation of routing algorithms. Additionally, from the experimental results, the conclusion is that DEBR is robust for several event generation functions. In summary, the proposed algorithm has several desirable properties. First, it is simple and localized, supporting scalability. Second, the algorithm maintains energy efficiency for networks while keeping an energy balance. Third, the algorithm is robust to diverse event generation patterns.

The lifetime of sensor networks is one of the most popular measurements to evaluate routing algorithms. Although this work defines the lifetime of sensor network as \( L_1 \), \( L_{10} \), \( L_{20} \), the definition of lifetime can vary according to the objective and nature of sensor network. Therefore, one can investigate the use of more delicate measurements which could be generally accepted. Also, in this work, we consider that energy is the most critical performance measure. However, in some applications, latency or routing path length becomes more important. It is obvious that hierarchical routing generates shorter path length than the proposed approach with sacrificing its solution space because hierarchical approach just considers a two-length routing path (sensor – cluster header – base station). In other words, a tradeoff between latency and energy balance exists. Therefore, it is more reasonable to consider two metrics simultaneous in designing a routing algorithm which is applicable to many wireless sensor network applications. Future work will involve development of routing algorithms with multi-criteria which can be applied to many sensor network applications.

In addition, although this study considers a general multi-hop communication scenario, where only a few sensors can communicate with the base station, a more specific problem definition and routing algorithm for this scenario is required. To apply the proposed algorithm to the general case, additional routing policies for sensors not able to communicate with the base station directly is necessary. In other words, sensors far from the base station need a different routing scheme to send their data to one of sensors in the area where sensors can communicate with the base station. Future work will advance the DEBR to apply to the general scenario and investigate how well the new DEBR works in the scenario.

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