Spanning Tree of Residual Energy Based on Data Aggregation for Maximizing the Lifetime of Wireless Multimedia Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) consist of small low-cost sensor nodes with limited energy. Because of the inherent energy constraint, prolonging the lifetime of a WSN is an essential challenge in research and practice. Wireless Multimedia Sensor Networks (WMSNs), a special type of WSNs, mainly focus on cooperatively passing their complex multimedia data such as pictures or video to base stations. However, two key factors must be considered in designing routing algorithms in WMSNs. The first one is the energy cost for data aggregation, which is not negligible but comparable to transmission cost in WMSNs. The other key factor is the complex data aggregation behavior that results in various compression ratios. In this paper, we propose a hierarchical routing algorithm, Spanning Tree Of Residual Energy (STORE), which considers these two important factors. We studied four different types of data aggregation models, and the simulation results indicate that our algorithm achieves a better lifetime than traditional routing algorithms such as SPT, MST, MTE, PEGASIS, LEACH, and PEDAP-AP.

Keywords
Wireless Multimedia Sensor Networks, Data Aggregation, Routing, Spanning Tree, Residual Energy

1. Introduction

More recently, interest in Wireless Sensor Networks (WSN) research has been shifting to Wireless Multimedia Sensor Networks (WMSNs) (Akyildiz et al., 2007) to reflect the advanced development of new Micro-Electro-Mechanical Systems (MEMS) technology, which has led to the availability of small, low cost, low power, and high computing power wireless sensor devices. The research on data gathering in WMSNs for images or video of the environment has given us new opportunities and challenges. As shown in Figure 1, a WMSN consists of a large number of sensor nodes that can communicate with each other and external Base Stations (BSs) responsible for collecting the sensed multimedia data. In the sensor, a power unit (battery) provides the essential power to activate other units such as CPU, memory, and communication devices. However, the battery is usually non-replenishable, thus the lifetime of WMSNs is finite.

One of the primary methods that have been widely used to enhance the lifetime of WMSNs and achieve network scalability is data aggregation (fusion)(Akkaya et al., 2008, Fasolo et al., 2007, Luo et al., 2007). In many WMSN applications, data aggregation has been proven to be a promising technique for reducing the amount of data in WMSNs and efficiently organizing WMSNs. Regardless of the data aggregation techniques employed, most existing algorithms assume that the data aggregation cost negligible, especially when fully-aggregation routing is used. Fully-aggregation routing (Fasolo et al., 2007) refers to that the amount of outgoing packet always remains the same regardless of the number of children of the relay node. For example, suppose sensors are distributed in order to measure the highest temperature over the area of interest. Instead of forwarding many data packets, the relay node compares the values and sends the highest value in one single packet. However, data aggregation in WMSNs is not negligible and is often

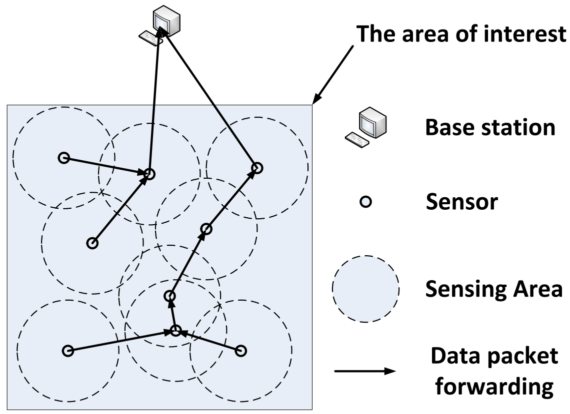

Figure 1: Illustration of a typical WSN

on the order of tens of nJ/bit (Luo et al., 2006), which is comparable to the transmission cost. Second, the amount of outgoing packet of each sensor varies due to the complex data aggregation behavior in WMSNs, especially when not every sensor generates the data packet. These two factors, the energy cost for data aggregation and the varying amount of outgoing packets, have not been major concerns in mainstream research on traditional WSNs.

We propose a novel routing algorithm, called Spanning Tree Of Residual Energy (STORE), which takes into account these two important factors. STORE uses a spanning tree to deliver data packets through sensors having higher residual energy than others and selects the next relay nodes according to the historical record of the amount of data packets. To the best of our knowledge, STORE is the first algorithm to maximize the lifetime of the WSN when the aggregation cost, aggregation ratio, and residual energy balancing are considered at the same time. STORE acts as a general solution to prolong the lifetime under different data aggregation models. In the numerical experiments, four different data aggregation models are used to validate the adaptability and flexibility of STORE, and it is evidenced that STORE significantly outperforms traditional routing algorithms, such as SPT, MST,MTE, PEGASIS, LEACH, and PEDAP-AP.

2. Related Work

LEACH (Heinzelman et al., 2002), the first original clustering algorithm for WSNs, uses randomized rotation of cluster heads to assign equal data aggregation and transmission loads among sensors in a WSN. After selecting the cluster heads, LEACH uses the nearest neighbor principle to organize the clusters. The cluster members directly transmit sensory data to the cluster head. In the cluster heads, these data are then fused, processed, and sent to the BS through direct communication. In PEGASIS (Lindsey et al., 2002), a chain-based algorithm, the only leader node collects the data from the chain and directly communicates with the BS in each round. To construct the chain, PEGASIS uses a greedy algorithm that starts with the farthest node from the BS. The selected node chooses the closest neighbor as its parent and the next node; thereafter the greedy algorithm is repeatedly performed among the unvisited nodes. The leader is randomly chosen to evenly distribute the energy expenditure among the sensors. The main advantage of PEGASIS is the long chain, which greatly reduces the total amount of data packets.

Shortest Path Tree (SPT) were proposed in (Krishnamachari et al., 2002). In SPT, each sensor sends its data packet to the BS via the shortest path, which can be computed by Dijkstra's algorithm (Cormen et al., 2009), and the data are aggregated at the intersections of paths. In MTE, described in (Heinzelman et al., 2002), each sensor chooses the path with minimum transmission energy consumption, E_{TX}. Take three nodes A, B and C as an example: node A will transmit a data packet to node C via node B if $E_{TX}(d_{AB}) + E_{TX}(d_{BC}) < E_{TX}(d_{AC})$. When the transmission energy is only a d^2 power loss, the equation can be simplified as $d_{AB}^2 + d_{BC}^2 < d_{AC}^2$. Minimum Spanning Tree (MST) (Cormen et al., 2009) is a traditional problem that seeks a spanning tree whose total weight is minimized.

Tan and Korpeoglu (2003) proposed Power-Efficient Data Aggregation Algorithms (PEDAP), as well as its power-aware version, PEDAP-PA. First, PEDAP builds up the link cost matrix, similar to the transmission energy consumption, and uses Prim's minimum spanning tree algorithm (Cormen et al., 2009) to compute the routing topology with the BS as the root. PEDAP-PA uses a slightly modified link cost, $EC_{ij} = \frac{C_{ij}}{e_i}$, where C_{ij} is the original link cost and e_i

is the remaining energy of node i. This algorithm would be periodically recomputed every certain number of rounds (for example, 100 rounds). Tan et al. (2011) also proposed a distributed version, localized PEDAPs (L-PEDAPs) based on LMST topology control.

Finally, Luo et al. (2006) provide an excellent point of view of the data aggregation. Their experiments showed that the energy cost for data aggregation in WMSNs remains at roughly 80 nJ/bit, which is sufficient in regard to the transmission energy cost. On the basis of this fact, Luo et al. (2006) took the aggregation cost into account and proposed AFST, which dynamically evaluates whether data aggregation is worthwhile; sometimes directly relaying the data to the BS is more efficient than performing data aggregation at certain nodes. If aggregation provides no benefit to the sensor network, SPT without data aggregation is used for the remaining routes.

3. System Model

Before introducing our algorithm, we first describe the preliminary assumptions of our model and define our problem in this section.

3.1 Preliminaries: Definitions, Notations and Assumptions

In this paper we evaluate wireless sensors that are randomly scattered on a two-dimensional, finite plane with a BS. The WMSN system can be modeled as a directed graph: $\mathfrak{G} = (V, L)$, where V refers to the set of all communication nodes; thus $V = S \cup BS = \{v_1, v_2, \ldots, v_{|S|+1}\}$, where S is the set of sensor nodes $\{s_i\}$, $i = 1, \ldots, |S|$. Because BS is the only base station, we specify that $\{v_1, v_2, \ldots, v_{|S|}\} = \{s_1, s_2, \ldots, s_{|S|}\}$ are sensor nodes and $v_{|S|+1} = BS$. L refers to the set of directed links $\{l_{ij}\}$, where $l_{ij} = \langle v_i, v_j \rangle \in \{0, 1\}$, and $v_i, v_j \in V$, from v_i to v_j. The value of l_{ij} is one if v_j is located within the limited circular transmission range of v_i, r; otherwise, it is zero. We consider a discrete-time WMSN system where the minimum time unit is a round (index is t), which is defined as the time period sufficient for collecting the data packets from the sensors in the WMSN and relaying the aggregated packets to the BS (Heinzelman et al., 2002). Further, $e^0(s_i)$ denotes the initial energy of sensor s_i; and $e^t(s_i)$ refers to the residual energy of sensor s_i at round t.

In this research, we make the following assumptions:

- One stationary BS with infinite energy is located within or away from the area of interest, and its transmission range is also set to infinity.
- Each sensor is fixed and has a unique predefined ID, which is used to distinguish the source of packets and to define parent-children relationships.
- Each sensor is equipped with an non-replenishable battery, and the sensors are homogeneous with the same initial energy level $e^0(s_i)$ (or e^0 for simplicity).
- We consider a periodical sensor network in which sensors periodically sense the environment and some of them report the sensed data packets to the BS. The sensor nodes that generate the raw data packets are called as source nodes, and the amount of data packet generated from every source node is assumed to be μ uniformly across sensors.

3.2 Data Aggregation Models

Sensors can be used not only as relays but also for measuring, collecting and aggregating data. We use $x(s_i)$ to denote the amount of data packet transmitted from sensor s_i. In specific, $x(l_{ij})$ denotes the amount of outgoing data packet on the link from s_i to s_j. Because of the aggregation process, we use $\tilde{x}(s_i)$ for the amount of temporary data before aggregation distinguishing it from the aggregated data $x(s_i)$. In addition, $\dot{x}(s_i) \in \{0, \mu\}$ refers to the amount of raw data generated by s_i itself; it is μ if s_i is a source node; otherwise, it is zero. Then, $\tilde{x}(s_j)$ can be given by $\tilde{x}(s_j) = \dot{x}(s_j) + \sum_{s_i \in N_j} x(l_{ij})$ as the sum of the amount of incoming packets and the raw data generated by itself, where $x(l_{ij})$ is the transmission data from s_i belonging to the set of the children of s_j, N_j. The transformation function $x(s_j) = f(\tilde{x}(s_j))$ will be discussed later in this section. If it is necessary to specify the amount of data packet of s_i at round t, we use $x^t(\cdot)$.

In this paper, we consider the foreign-coding method: it encodes the children's data packets by using the local data as side information. Let the correlation coefficient ρ_{ij} be a spatial correlation function between s_i and s_j in terms of d_{ij}, then the approximate joint entropy (Pattem et al., 2008) is modeled as

$$x(s_j|s_i) = f(\dot{x}(s_j) + x(l_{ij})) = \dot{x}(s_j) + (1 - \rho_{ij}) \cdot x(l_{ij}), \tag{1}$$

where $x(s_j|s_i)$ is the amount of aggregated joint data packet when s_j receives the data packet from its child s_i. In this foreign-coding model, the entropy of the passed data packet $x(l_{ij})$ is reduced by the ratio $(1-\rho_{ij})$; however, the entropy of the data from the aggregation node $\dot{x}(s_j)$ treated as side information, is not reduced. However, the condition is slightly different when the relay node does not have local data (it is not a source node) as its side information if it has data packets coming from at least another two nodes. It will use one of the data packets as the side information for computing the joint entropy for the entire set. We accept the constructive iterative algorithm in (Pattem et al., 2008) for computing the joint entropy of a set of spatially correlated sensors: in each iterative stage, the added data packet contributes uncorrelated data to the entropy of the aggregated data of the set of sensors.

According to the definition of ρ_{ij}, various data aggregation models can be constructed that mimics various data aggregation behaviors, as follows:

- Full aggregation model: A simple function is used in the aggregation process, such as maximum, minimum, or average function (Heinzelman et al., 2002, Lindsey et al., 2002). For example, if we want to know the highest temperature in the target area in a supervisory application, the MAX function would be suitable for that purpose. This kind of data aggregation model is called full aggregation model (Luo et al., 2007), which means that the amount of output packets is the same no matter how many input data packets there are because the relay node only outputs the summarized data. In this case, the value of ρ_{ij} can be seen as one, because the aggregated data amount is always equal to the amount of the side information, $x(s_j|s_i) = \dot{x}(s_j)$. Traditionally, the aggregation energy cost of the full aggregation model is on the order of nJ/bit, which is one-tenth the power consumed for data transmission. Therefore, it has been even neglected.

However, the value of ρ_{ij} being not one is commonly observed in Wireless Multimedia Sensor Networks (WMSNs), e.g., in image aggregation or video stream aggregation. This type of data aggregation demands more CPU resources and energy which is usually on the order of tens of nJ/bit (Luo et al., 2006). We list the other four popular data aggregation models below:

- Simple correlation model (Cristescu et al., 2006):
$$\rho_{ij} = \rho, \tag{2}$$
where ρ is a constant. The simple correlation model assumes that ρ_{ij}, simplified to ρ, has no relationship with d_{ij}, the distance between s_i and s_j, and the amount of data packets is reduced at a constant ratio at the relay node.

- Power exponential correlation model (Berger et al., 2001):
$$\rho_{ij} = \exp(-d_{ij}/\theta)^n, \tag{3}$$
where θ is a constant parameter denoting the degree of correlation.

- Inverse distance model (Berger et al., 2001):
$$\rho_{ij} = \frac{1}{1+\frac{d_{ij}}{\theta}}. \tag{4}$$

- Spherical correlation model (Berger et al., 2001):
$$\rho_{ij} = \begin{cases} 1-\frac{3}{2}\frac{d_{ij}}{\theta}+\frac{1}{2}(\frac{d_{ij}}{\theta})^3 & \text{if } \frac{d_{ij}}{\theta} \le 1 \\ 0 & \text{if } \frac{d_{ij}}{\theta} > 1. \end{cases} \tag{5}$$

Except for the full aggregation model and the simple correlation model, the basic idea behind the models is the same: the closer the two sensors are, the more correlated the data is. A more detailed understanding of the relationships can be gained from Figure 2. When d_{ij} increases, ρ_{ij} approaches zero, which means that the two nodes are less correlated. The power exponential correlation model is typically used to simulate electromagnetic waves or other physical phenomena. It assumes that the strength of an electromagnetic wave decreases with the inverse square of the distance in two-dimensional space ($n = 1$ or 2 is often used in applications). The inverse distance model is a simplified version of the power exponential model, which can be obtained using the first-order Taylor series. The spherical correlation model simulates an electromagnetic wave from a point source that propagates as a continuously extending globe in three-dimensional space; as a result, the correlation coefficient in the spherical correlation model attenuates more rapidly compared to other models. The other distinctive popular feature of the spherical correlation model is that any two data packets are seen as uncorrelated when they are separated by more than θ. The adequacy of correlation models depends on the geographical dependencies of the collected data in the target environment.

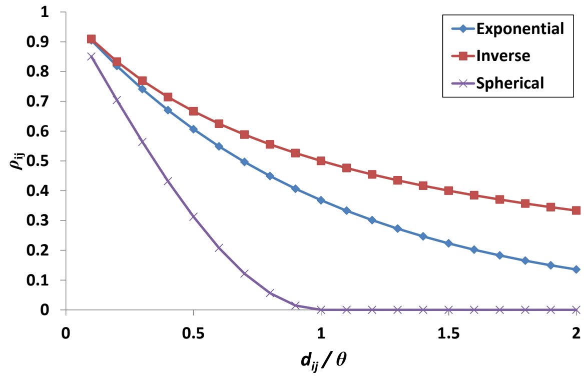

Figure 2: Correlation coefficient (ρ_{ij}) versus different normalized distances (d_{ij}/θ)

3.3 Energy Model

In this paper, we use the First Order Radio Model for every assumption, as it is popularly adopted in (Heinzelman et al., 2002, Lindsey et al., 2002, Luo et al., 2006, Tan and Korpeoglu, 2003, Wu et al., 2008). In the model, the energy dissipation consists of three main components: the energy spent by s_i in transmitting, receiving, and aggregating data, as shown in Equation 6.

$$E_{TX,s_i}(x(s_i), d_{ij}) = \varepsilon_{tx} \cdot x(s_i) + \varepsilon_{amp} \cdot x(s_i) \cdot d_{ij}^n, \tag{6a}$$

$$E_{RX,s_i}(\tilde{x}(s_i)) = \varepsilon_{rx} \cdot \tilde{x}(s_i), \tag{6b}$$

$$E_{AG,s_i}(\tilde{x}(s_i)) = \varepsilon_{ag} \cdot \tilde{x}(s_i). \tag{6c}$$

s_i consumes $E_{TX,s_i}(x(s_i), d_{ij})$ in transmitting an $x(s_i)$-bit data packet to another sensor s_j, where d_{ij} is the distance between sensor s_i and s_j. ε_{tx} denotes the energy consumption per bit on the transmitter circuit and ε_{amp} denotes the characteristic constant in the transmit amplifier.

The power of the exponent, n, depends heavily on the design of the transmit electronics and the external environment, usually ranging from 2 (free-space propagation) to 4. E_{RX,s_i} denotes the energy consumption for receiving $\tilde{x}(s_i)$-bit data packet from its children, N_i, and itself. E_{AG,s_i}, the energy consumption due to data aggregation, is proportional to $\tilde{x}(s_i)$. Equation 6 assumes that the sensors have omni-directional antennas and can adjust their transmission power to use the minimum energy to communicate with other sensors or BS. ε_{tx}, ε_{rx} and ε_{ag} are tunable parameters depending on the applications.

3.4 Problem Definitions

The definition of the lifetime is application-oriented, and the threshold varies depending on the application for which the WSN is being used. Some applications are critical and cannot tolerate any loss of sensors, whereas others require only a subset of live nodes. Our primary definition of lifetime is the time until the first sensor dies as it is widely accepted in literature (Al-Karaki and Kamal, 2004).

4. STORE: Spanning Tree Of Residual Energy

4.1 Details of STORE

We summarize the requirements in designing a routing algorithm in WMSNs: (1) energy-efficient selection mechanism, (2) capability of dynamic topology construction, (3) energy-aware mechanism, (4) prediction mechanism of the amount of data packets, and (5) adaptability for different data aggregation and energy consumption behaviors. In this section, we propose the algorithm STORE which considers and integrates the above issues, and it is summarized as follows: First, STORE is based on the minimum spanning tree rooted at the BS which is an energy-efficient spanning tree. Second, STORE dynamically reconstructs the spanning tree at the beginning of each round. The key issue here is the design of the weight matrix by which the spanning tree is composed. The weights of individual links are represented in Current Residual Lifetime (CRL) as detailed below.

First, we have designed a metric, Predictive Energy Cost (PEC), which estimates the energy consumption of individual sensors in a round. We define PEC as follows:

$$pec^t(s_i,s_j) = E^t_{TX,s_i}(x^t(s_i),d_{ij}) + E^t_{RX,s_i}(\tilde{x}^t(s_i)) + E_{AG,s_i}(\tilde{x}^t(s_i)), \tag{7}$$

where $pec^t(s_i,s_j)$ is the PEC of s_i at round t when its next relay is s_j, which is the summation of the transmission, reception, and aggregation energy costs. The argument is that $pec^t(s_i,s_j)$ is computable if the routing topology and both $x^t(s_i)$ and $\tilde{x}^t(s_i)$ are known.

Next, we define the Current Residual Lifetime (CRL) of s_i at round t when its next relay is s_j, $crl^t(s_i,s_j)$, as follows:

$$crl^t(s_i,s_j) = \frac{e^t(s_i) - pec^t_{ij}}{pec^t_{ij}}. \tag{8}$$

The CRL integrates the residual energy and the energy costs of aggregation, transmission, and reception into a single metric. The physical meaning of CRL is the residual lifetime (in rounds) of s_i under the current residual energy and routing topology. For example, when we talk about how much gasoline is left in a vehicle, we usually do not say three liters are left; instead, we say that the car can still run for another 90 miles. Because of the characteristics of the spanning tree structure, the nodes closer to the BS will consume more energy upon transmitting, receiving, and aggregating the data than the nodes far from the BS because of the cumulative amount of data packets. Therefore, the maximization of CRL is an appropriate solution to maximize the lifetime. For this purpose, we pursue the maximization of spanning tree, denoted as MaxST, in order to obtain a spanning tree where no sensor uses considerably more energy than any other sensor in the spanning tree.

However, in order to compute MaxST, we have to input $x^t(s_i)$ and $\tilde{x}^t(s_i)$ to the computation of PEC. To solve it, we use historical records to predict the amount of transmission and reception data. We define the Predictive Amount of Data (PAD) in Equation 9.

$$\frac{1-\beta}{1-(\beta)^{t-1}} \cdot \sum_{k=1}^{t-1} (\beta)^{k-1} x^{t-k}(s_i) \rightarrow x'^t(s_i), \tag{9a}$$

$$\frac{1-\beta}{1-(\beta)^{t-1}} \cdot \sum_{k=1}^{t-1} (\beta)^{k-1} \tilde{x}^{t-k}(s_i) \rightarrow \tilde{x}'^t(s_i), \tag{9b}$$

where $x'(\cdot)$ and $\tilde{x}'(\cdot)$ are the predictive amounts of transmission data and reception data, respectively. β is the learning rate that puts a more weight on a more recent record ($0 \leq \beta \leq 1$). $\frac{1-\beta}{1-(\beta)^{t-1}}$ is the normalization factor. The resulting $x'^t(s_i)$ and $\tilde{x}'^t(s_i)$ can be used as input to Equation 7.

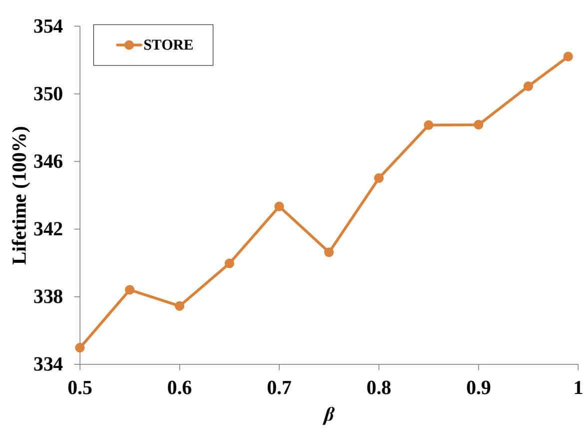

Figure 3: Performance of STORE for various β values

However, in the simulation experiments, we found that the performance improves when β approaches one (see Figure 3). This phenomenon strongly implies that every past record should be equally treated with the same weight. When all of the sensors smoothly deplete their residual energy, the amount of transmission and reception data packets does not vary significantly and is dominated by the geographical locations. When β approaches one, Equation 9 can be simplified as follows:

$$\lim_{\beta\to 1} \frac{1-\beta}{1-(\beta)^{t-1}} \cdot \sum_{k=1}^{t-1} (\beta)^{k-1} x^{t-k}(s_i) \tag{10a}$$

$$= \lim_{\beta\to 1} \frac{1}{\underbrace{1+\beta+\ldots+(\beta)^{t-2}}_{\text{t-1 times}}} [x^{t-1} + \beta x^{t-2} + \ldots + (\beta)^{t-2} x] \tag{10b}$$

$$= \frac{1}{t-1} \sum_{k=1}^{t-1} x^k(s_i) \to x'^t(s_i) \tag{10c}$$

That is, the weight for every past record is the same, which is $\frac{1}{t-1}$, thus $x'^t(s_i)$ is simply the average of the past records. Note that all $x'^1(s_i)$ are set as μ for initial predictions. We also recognize the recursive relation in Equation 10. Using the recurrence relation, we can simplify the PAD as Equation 11a:

$$\frac{1}{t-1}[x^{t-1}(s_i) + x'^{t-1}(s_i) \cdot (t-2)] \to x'^t(s_i) \tag{11a}$$

$$\frac{1}{t-1}[\tilde{x}^{t-1}(s_i) + \tilde{x}'^{t-1}(s_i) \cdot (t-2)] \to \tilde{x}'^t(s_i) \tag{11b}$$

Following the same procedure, Equation 9b can be simplified as Equation 11b. Because of its simplicity and efficiency, we use Equation 11a and 11b to predict the amount of transmission and reception data. We then adopt the Prim's algorithm (Cormen et al., 2009), which is a well-known MST algorithm, in constructing the MaxST.

5. Numerical Experiment

In this section, to evaluate the performance of STORE, we select six different routing algorithms for comparison: SPT, MST, MTE, PEGASIS, LEACH, and PEDAP-AP, which are illustrated in Section 2. SPT, MST, MTE, and PEDAP-AP are tree-based algorithms, PEGASIS is a chain-based algorithm, and LEACH is a cluster-based algorithm. Among these routing algorithms, SPT, MST, and MTE are without any energy-aware mechanism. PEDAP-AP, PEGASIS and LEACH are equipped with some kind of energy-aware mechanism. PEDAP-AP is also using spanning tree, but the weight is based on only transmission cost and it uses a constant value μ for the amount of data packets. The lifetime until the first sensor dies is our main metric to evaluate the performance and we denote it as lifetime(100%). The experiments were performed using a simulator implemented in MATLAB 7.7.

5.1 Experimental Setup

We use the simulation parameters as described in Table 1. We randomly place 100 sensor nodes in a $100 \times 100m^2$ two-dimensional square plane, and the BS is located at $(50m, 100m)$. The initial energy e^0 for each sensor is 0.5 Joule and the sensing radius is 10 meters. Designed for wireless 2.4 GHz IEEE 802.15.4 networks, sensors have a maximum radio range of 300 m. The data packet size μ from a source node and the control information packet size are 5000 bits and 128 bits, respectively. The probability to generate a data packet (i.e. to become a source node) by each sensor in each round is fixed at 60%. ε_{elec}, ε_{tx}, ε_{rx}, ε_{ag}, and n are used for describing the First Order Radio Model, discussed in Equation 6. The simulations are repeated 100 times for every scenario.

5.2 Simulation Results

In overall, the simulation results are very positive. As shown in Figure 4, STORE dominantly outperforms the other six algorithms in all different definitions of lifetime under the power exponential correlation model with $\theta = 20$. STORE performs better than SPT, MST, MTE, PEGASIS, and LEACH by approximately 148.7%, 105.4%, 310.0%, 1072.4 %, and 2134.6 %, when taking Lifetime (100%) as the metric, respectively. The improvements are less when compared to PEDAP-AP, which also has a dynamic spanning tree routing topology. STORE, equipped with a mechanism to predict the data amount, still shows improvement by 11.83%.

Next, we examined the adaptivity and flexibility of STORE under different data aggregation models. Figure 5a shows that the performance of STORE was significantly better than that of SPT, MST, MTE, PEGASIS, LEACH, and PEDAP-AP under the simple correlation model with different ρ values varying from 0.1 to 0.9. The performance of STORE is up to 3106% better than the original LEACH.

Since STORE is significantly better than other algorithms except for PEDAP-AP in terms of performance, we only state the performance difference between STORE and PEDAP-AP. Figure 5b shows that the performance of STORE

Table 1: Basic simulation parameters

Parameter	Value
Target area	$100 \times 100\ m^2$
Number of sensor nodes	100
Initial energy (e^0)	0.5 $Joule$
Location of the BS	$(50m, 100m)$
Data packet size (μ)	5000 $bits$
Information packet size	128 $bits$
Sensing radius	$10m$
ε_{elec}	50 nJ/bit
ε_{tx}	50 nJ/bit
ε_{rx}	50 nJ/bit
ε_{amp}	100 $pJ/bit/m^n$
ε_{ag}	80 nJ/bit
n	2.5
Probability of generating data packets	60%
Maximum radio range	300 m

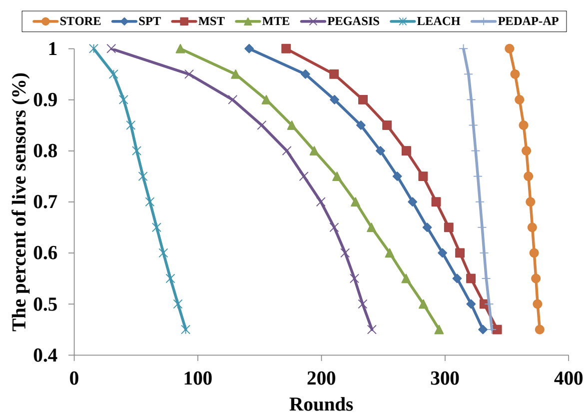

Figure 4: Percentage of live nodes over time (rounds) under the power exponential correlation model with $\theta = 20$

over PEDAP-AP increases with an increase in the θ value: The performance ratios of STORE to PEDAP-AP are 6.98%, 11.13%, 11.83%, 11.94%, and 12.33%, for θ values of 10, 15, 20, 25, 30, respectively.

Results shown in Figures 6a and 6b are entirely consistent with those reported in the previous results. STORE steadily outperforms PEDAP-AP by up to 13.67%. The only exception is when θ is 10 in the case of the spherical correlation model. In this case, most of the data packets are not aggregated because most distances are more than θ. In this scenario, the data aggregation loses its effectiveness.

6. Conclusion

We developed a novel tree-based routing algorithm, STORE, which constructs a dynamic energy-balanced spanning tree that takes the residual energy, aggregation cost, and the predictive data amount into consideration. STORE offers a simple but effective learning mechanism that uses the historical records to predict the amounts of data packets received and transmitted.

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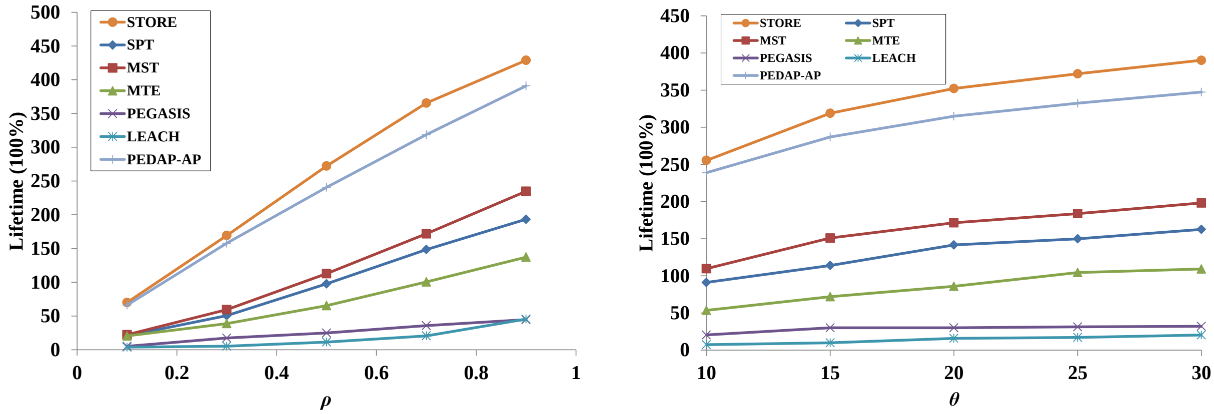
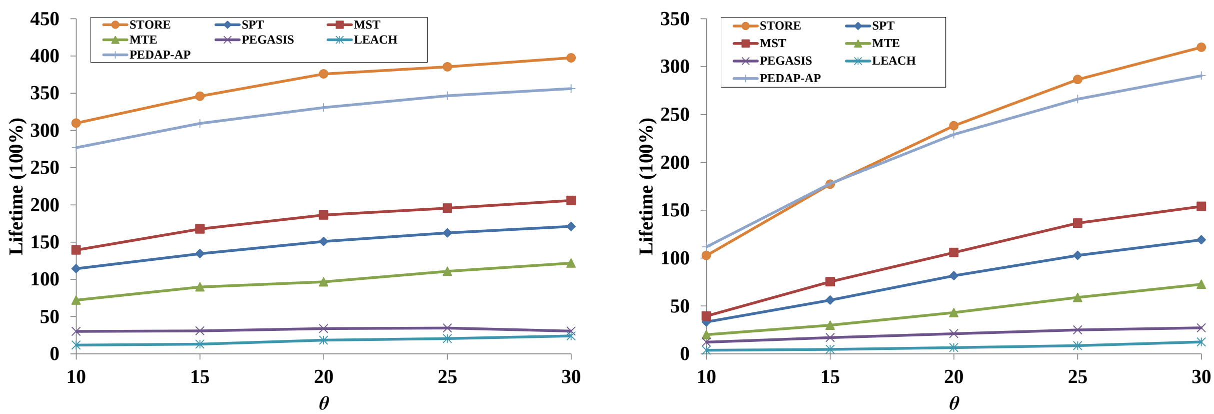


(a) Performance comparisons using different ρ values under the simple correlation model.

(b) Performance comparisons under the power exponential correlation model with different θ values

Figure 5: Performance comparisons under the simple and power exponential correlation models



(a) Performance comparisons under the inverse distance model with different θ values.

(b) Performance comparisons under the spherical correlation model with different θ values

Figure 6: Performance comparisons under the inverse distance and spherical correlation models

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