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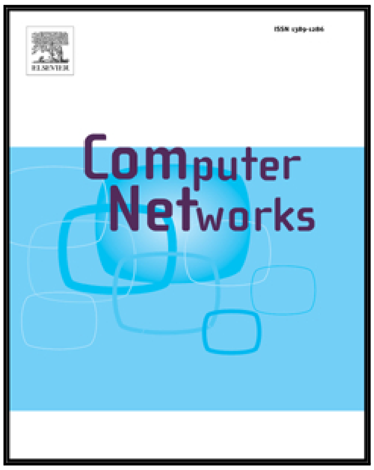

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PII: S1389-1286(18)30130-0
DOI: 10.1016/j.comnet.2018.03.016
Reference: COMPNW 6443

To appear in: *Computer Networks*

Received date: 3 August 2017
Revised date: 26 February 2018
Accepted date: 15 March 2018

Please cite this article as: Mahdi Zareei, Cesar Vargas-Rosales, Rafaela Villalpando-Hernandez, Leyre Azpilicueta, Mohammad Hossein Anisi, Mubashir Husain Rehmani, The Effects of an Adaptive and Distributed Transmission Power Control on the Performance of Energy Harvesting Sensor Networks, *Computer Networks* (2018), doi: 10.1016/j.comnet.2018.03.016

The Effects of an Adaptive and Distributed Transmission Power Control on the Performance of Energy Harvesting Sensor Networks

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Abstract

The design of routing protocols for wireless sensor networks (WSNs) has been traditionally tackled by assuming battery-powered sensors, in which minimizing the power consumption was the main objective. Advances in technology and the ability to harvest energy from the environment has enabled self-sustaining systems and thus diminish the significance of network lifetime considerations in the design of WSNs. Although WSNs operated by energy-harvesting sensors are not limited by network lifetime, they still pose new design challenges due to the unstable and uncertain amount of energy that can be harvested from the environment. In this paper, we propose a new protocol for energy-harvesting sensor networks that uses adaptive transmission power to maintain the network connectivity, and distributes the traffic load on the network. Based on local information, each node dynamically adjusts its transmission power in order to maximize the network's end-to-end performance. The simulation results indicate that the proposed protocol keeps the network connected at most of the times by using an efficient power management, outperforming greedy forwarding and dynamic duty cycle protocols in terms of packet delivery ratio, delay, and power management.

Keywords:
Energy harvesting, wireless sensor network, transmission power control, energy efficiency, green computing

1. Introduction

Ubiquitous sensing enabled by evolution of Wireless Sensor Network (WSN) technologies affects many areas of our daily lives. The ability of sensors to measure, infer, and understand environmental conditions let us think about the seamless integration and proliferation of sensors

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and actuators in everyday objects. Connecting these objects to the Internet to share information with other services and people at the large scale, triggers the concept of Internet of Things (IoT), [1]. These uniquely identifiable heterogeneous devices aim to make the Internet ubiquitous and pervasive, and open the possibilities to have several smart applications such as health care [2], smart transportation [3], smart environment monitoring [4], home automation [5], and many more.

In sensor networks, one of the main challenges is the efficient use of energy, and although most of the applications of sensor networks require little power, relying on the sensor's low capacity power source is not the way that long-term operation can be reached without human intervention. Even by having the most efficient energy use, the lifetime of the network is still limited by the energy capacity of the batteries. Besides, the batteries also experience leakages that drain the resources even when they are not used, not to mention the environmental damage caused by the leakages, [6]. In several of these applications, such as smart environment monitoring, a high number of sensor/actuators perform control and monitoring tasks in harsh, unreachable or difficult to access areas. For successful implementation of these applications, WSN devices (as building blocks of IoT) should be produced cheap, communicate autonomously, and operate for a long time without any need of human intervention. These prerequisites imply strict requirements in power management of IoT devices to ensure their "perpetual" operation. Therefore, it is important to improve the energy efficiency and durability of devices in IoT.

Another challenge that an energy-harvesting network might face is having some part of the network disconnected due to sensor nodes that have not enough energy. This problem specially can arise when we have a single Fusion Center (FC), where all the nodes forward packets towards it. In WSNs, the energy of the nodes that are closer to the FC deplete faster as they handle most of the traffic compared to that of other nodes. One of the main objectives of green computing is the efficient consumption of energy in WSNs, by providing solutions that improve performance of the network, and at the same time decrease energy consumption to extend the network lifetime. Aside from relying on revolutionary developments of battery technologies, one of the most important ways to improve the system lifetime is to harvest energy from ambient environmental energy sources, [7]. We are using energy harvesting (EH) enabled devices in our lives, e.g., a desk calculator using a solar cell is an example of an energy harvesting device. An energy harvesting sensor node is a node that draws part or all of its energy from the environment. The main advantage of this energy in comparison to the stored energy from the batteries is that the harvested energy is potentially infinite, although there may be a limitation on the rate at which it can be used, [8]. There are many commercially available energy transducers that can harvest ambient energy such as radio-frequency harvesting devices, that can convert received radio signals to DC power, or piezoelectric harvesting devices that convert mechanical energy into electrical energy.

However, due to the non-uniform distribution of ambient energy, the amount of available energy to be harvested varies over space and time. This uncertainty in harvested energy produces the need to have sensors with intelligent communication protocols that manage the harvested energy in the most optimal way. To achieve this goal, the efficiency of existing communication protocols need to be studied in the network with ambient energy harvesting. Moreover, new methods must be developed to help the nodes to adapt their power consumption profile automatically to increase the network adaptation.

The main objective of this paper is twofold: from the network point of view, we want to make sure that the network is connected, avoiding disconnections due to lack of energy in sensor nodes. From the harvested energy point of view, we want to use the available power in nodes in an efficient way to increase network performance. Therefore, in this paper, we propose Adaptive and Distributed Transmission Power Control (ADTPC), which is a novel cross-layer protocol for EH powered IoT applications that uses adaptive transmission power to improve the overall performance of the network. ADTPC scheme uses the information provided by the physical layer about the harvested energy as well as information provided by the MAC sublayer regarding the channel conditions to decide the best possible route to transfer the packets. The main concept of the proposed method is to increase the transmission range of the nodes that have higher levels of energy when neighboring relay nodes have low energy levels. At the same time, the protocol tries to avoid transmitting packets that use the nodes that are in critical energy levels. We also consider signal propagation conditions for every link for a more realistic communication, and compare the ADTPC to the greedy forwarding and the typical dynamic duty cycle techniques with energy harvesting. However, this method can be applied and used in any routing protocol or algorithm to improve end to end performance of the network. Using ADTPC, we show that the network maintains connectivity, and the packet delivery ratio can be maximized, while end-to-end delay is minimized.

The rest of this paper is organized as follows. Section 2 describes the related work in MAC and routing protocols for energy-harvesting sensor networks, highlighting the open issues and challenges. The proposed ADTPC protocol and the system model are introduced in Section 3. Section 4 discusses and analyzes the results obtained from performance evaluation. Section 5 introduces the statistical behavior of the connectivity in the network topology and shows how it is improved by the proposed protocol. Finally, the conclusions are in Section 6, where the contribution of the paper is summarized and future actions are highlighted.

2. Related Work

Typically, in battery powered devices, the power management design goal is to maximize the network lifetime by minimizing the energy consumption [9, 10], while dealing with performance constraints. Energy harvesting might be used as a supplement to the battery energy to maximize the lifetime. Otherwise, it can be used at an appropriate rate such that the system continues to operate perennially, which is called energy neutral operation mode, [11]. Although, IoT operated by energy-harvesting devices is not limited by network lifetime, it still poses new design challenges due to the unstable and uncertain amount of energy that can be harvested from the environment. This uncertainty imposes some serious networking-related design challenges in MAC and routing protocols.

The path selection in multi-hop WSNs is a challenging task. The shortest distance between the sender and the corresponding receiver is not always the best path to minimize energy consumption or end-to-end delay. Distributing the traffic among various network paths is a straightforward approach to maximize network lifetime in traditional WSNs. For routing in energy harvesting wireless sensor networks (EH-WSNs), several researchers have considered energy harvesting and consumption models in route decision making as a solution, [12]. Figure 1 shows the general classification of the routing protocols in EH-WSNs.

Voigt, et.al., [13], presented a routing scheme for solar powered sensors nodes. The algorithm searches and selects a minimum path between the sender and the receiver, and propagates all the traffic from the selected path preferably using solar powered nodes. The experimental results show that the solar-aware routing techniques improve energy efficiency in various network setups. Authors in [14] used different parameters such as residual energy on the rechargeable battery, replenishment rate and required energy for packet transmission as decision metrics for selecting routes.

Lattanzi, et.al., [15], proposed a different approach for extending and improving the minimum path routing for EH-WSNs. Randomized Weighted Minimum Path (R-WMP) integrates power requirement of each link and the number of hops for path selection. In another extension called Randomized Minimum Path Energy (R-MPE), an algorithm chooses the path that minimizes the energy consumption. In [16], authors proposed and extension for Low Energy Adaptive Clustering Hierarchy (LEACH), called Solar Low Energy Adaptive Clustering Hierarchy (sLEACH) routing in solar-powered sensor networks. The main idea is to give a higher probability to solar-powered nodes with high remaining energy to become cluster heads. The results indicated that this idea can improve the network lifetime significantly.

In [17], authors proposed Geographic Routing with Environmental Energy Supply (GREES) that considered the quality of the wireless links in addition to residual energy, energy consuming rate, energy harvesting rate, and distance to the receiver. Authors in [18] used duty cycling node and opportunistic forwarding as their routing scheme. When a sender broadcasts a data frame, any node that is closer to the sink and is available to forward traffic, rebroadcasts the frame. In this scheme, usually an energy profile of nodes is used to change the duty cycle of the nodes in the network. Thus, when nodes have higher levels of residual energy, they use higher duty cycle and when they have low levels of energy they reduce their duty cycle.

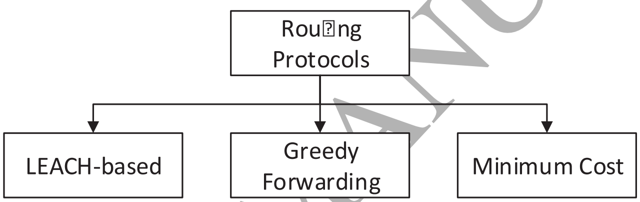

Figure 1: Classification of routing for energy-harvesting sensor networks

Cao, Yifeng, et.al., [19], proposed an energy harvesting routing (EHR) that uses residual energy and energy harvesting rate of the neighboring nodes to locally select the best optimal hop. In [20], authors proposed another LEACH based routing protocol that uses harvested energy and consumed energy ratio for cluster head (CH) selection, and gave to the harvested energy a higher priority. Dong, Yunquan, et.al., [21], present a cluster-based routing protocol, referred to as the distance-and-energy-aware routing with energy reservation (DEARER) where CH nodes participate relaying packets from non-cluster-head nodes to the sink. However, DEARER gives more priority to the nodes that are closer to the sink or have higher harvesting rate to become cluster heads.

The research community paid more attention to develop and design specific MAC protocols for EH-WSNs. Existing MAC protocols can be classified into two major approaches: synchronous and asynchronous (Figure 2). The main characteristic of synchronous MAC protocols is their requirement for time synchronization. Most of synchronous schemes employ duty-cycle operation. They use a scheduling algorithm to control the sleep and wakeup cycles of the nodes. Synchronous MAC protocols can be divided into three major paradigms: CSMA based, TDMA based and hybrid which is a combination of those two. In contrast to the synchronous approach, in the asynchronous scheme each node has a duty cycle that is independent of the rest of the nodes. Since asynchronous MAC protocols do not require synchronization and storing schedules, they have less storage and computation overheads compared to those of the synchronous scheme. It can be further divided into two major sub-categories, namely Preamble based (transmitter-initiated) and Beacon based (receiver-initiated).

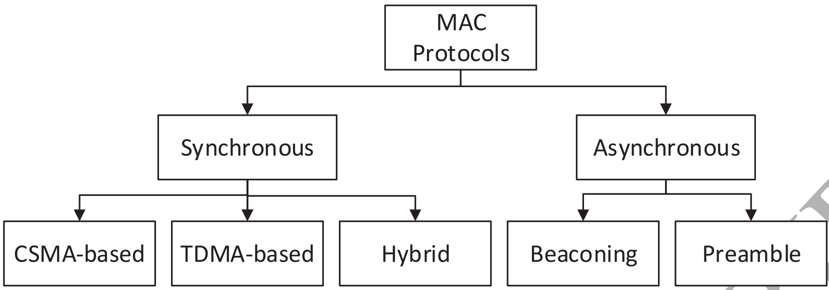

Figure 2: WSN MAC protocols classification

As it has been discussed, in EH-WSNs the amount of harvested energy varies for different nodes depending on time and space. Therefore, having a network-wide synchronization is not efficient, which makes synchronous MAC protocols not suitable to be employed for EH-WSNs. On the other hand, asynchronous MAC protocols can support individual schedules, making them more suitable to be employed for EH-WSNs. Among asynchronous approaches, researchers have shown that receiver initiated (beacon based) MAC protocols show lower idle listening periods, and are performing better for energy harvesting, [22]. There are several beacon-based MAC protocols proposed for EH-WSNs, some of which we describe in the following.

Energy Harvesting MAC (EH-MAC) [23], is a multi-hop receiver-initiated probabilistic polling MAC protocol for EH-WSNs. The idea comes from the unpredictability of energy harvesting, where receivers do not know which nodes are awake to perform the packet transmission, thus, instead of carrying the ID of a specific sensor, the polling packets contain a contention probability P_c parameter. If a node receives a polling packet, it compares the probability with its own randomly generated number to decide whether to remain in the receiving state or to switch to the charging state. Authors proposed two different schemes to adjust the dynamic contention probability namely Additive Increase Multiplicative Decrease (AIMD) and Estimated Numbers of Active Neighbors (ENAN) algorithms.

Energy Adaptive MAC (EA-MAC) [24] is proposed for single-hop WSNs powered by radio-frequency (RF) energy. A network formed in a star topology and an RF-emitting sink node (also called master node) transfer energy to surrounding EH nodes. The master node is always awake to distribute RF energy and receive data packets while sensor nodes use the node energy harvesting status to tune between active and sleep status. A node turns off its radio transmitter and puts its processor into the sleep state to save and harvest energy at the same time. A node changes status from sleep to active when the level of harvested energy is equal to the energy required to transmit a packet. In the active state, a node contends for the channel to perform data transmission using CSMA/CA scheme. Similar to the unslotted CSMA/CA algorithm in IEEE 802.15.4, a node adaptively manages the contention period using the Energy Adaptive Contention algorithm (EAC) to satisfy fairness, where back-off time is controlled by the average amount of harvested energy .

On Demand MAC (ODMAC) protocol, [25], is a beacon based, asynchronous MAC protocol proposed specially for EH-WSNs. As other beacon-based MAC protocols, each receiver periodically broadcasts a beacon, which indicates the receiver is ready to receive incoming packets. The nodes that have packets to send, listen to the channel for an appropriate beacon. After receiving a beacon, to avoid interference, nodes trigger a random back-off timer to wait. After the timer expires, the data transmission takes place. By finishing each successful transmission, the receiver starts sending a new beacon. Using this method, ODMAC eliminates the idle listening in the receiver side. ODMAC uses opportunistic forwarding method to reduce the packet delay. Instead of waiting for the specific beacon, if the transmitter receives any beacon from the node which is included in the list of potential forwarders, the transmitter starts forwarding a frame to the owner of the first beacon received. The list of potential forwarders is obtained from the routing protocol and usually includes all the nodes that are closer to the sink.

As one can see, most protocols do not use power control to save energy. In this paper, we study the effect of power control on the overall performance of the network using greedy forwarding method. Based on the network topology and node locations, different nodes in the network consume different amounts of energy, and possibly harvest different amounts of energy. Thus, having an adaptive transmission power control in energy harvesting sensor networks can be a suitable approach, which is studied in the following section.

3. Adaptive and Distributed Transmission Power Control (ADTPC)

Most of the routing protocols in battery powered WSNs focus on extending the network lifetime. However, in energy-harvesting sensor networks, the network lifetime is not bounded by the limited battery power. On the other hand, the stochastic and time-varying nature of the ambient energy source makes necessary to consider a dynamic routing algorithm that can adapt itself to the variation of availability of energy and environmental conditions. Therefore, a new set of objectives is necessary to be considered for routing in energy-harvesting sensor networks. This section introduces our approach for an efficient routing scheme, which efficiently uses the harvested energy to improve performance in energy harvesting sensor networks.

Our approach can be considered a data-centric routing protocol, which focuses on the aggregation of information from sensor nodes to the Fusion Center (FC). In the data-centric approach, usually the nodes that are closer to the FC are going to relay large amounts of traffic from the sensors on the outskirts of the network. Therefore, these nodes are going to deplete their energy faster than other sensors in the network. This situation is illustrated in Figure 3, where 50 nodes randomly distributed in a square of 500 meters per side form a network and the FC is placed at the center of the area. The lines between nodes indicate the working topology of the network based on greedy forwarding at each specific round of the simulation (indicated by the number enclosed by a rectangle). Red stars indicate the out of energy sensors and green squares indicate disconnected nodes. In this work we refer to "inactive nodes" as the nodes that run out of energy and are unable to operate until they harvest enough energy for the normal operation mode, and "disconnected nodes" as the nodes that have enough energy to transmit, but they have no route to the FC. As it can be seen, node 18 with coordinates $(x, y) = (279, 385)$, is relaying heavy traffic towards the FC and runs out of energy in round 70. Consequently, nodes 18, 48, 23, 9 and 33 are out of energy in round 156. It is interesting to see that all the traffic from the upper part of the network is relayed through node 3 with coordinates $(x, y) = (230, 311)$, and it is expected to run out of energy soon. As it is illustrated, in round 164 after several nodes near the FC run out of energy, many nodes become disconnected from the network. Therefore, our main objective with the proposed technique is to avoid having disconnected nodes in the network by using transmission power control.

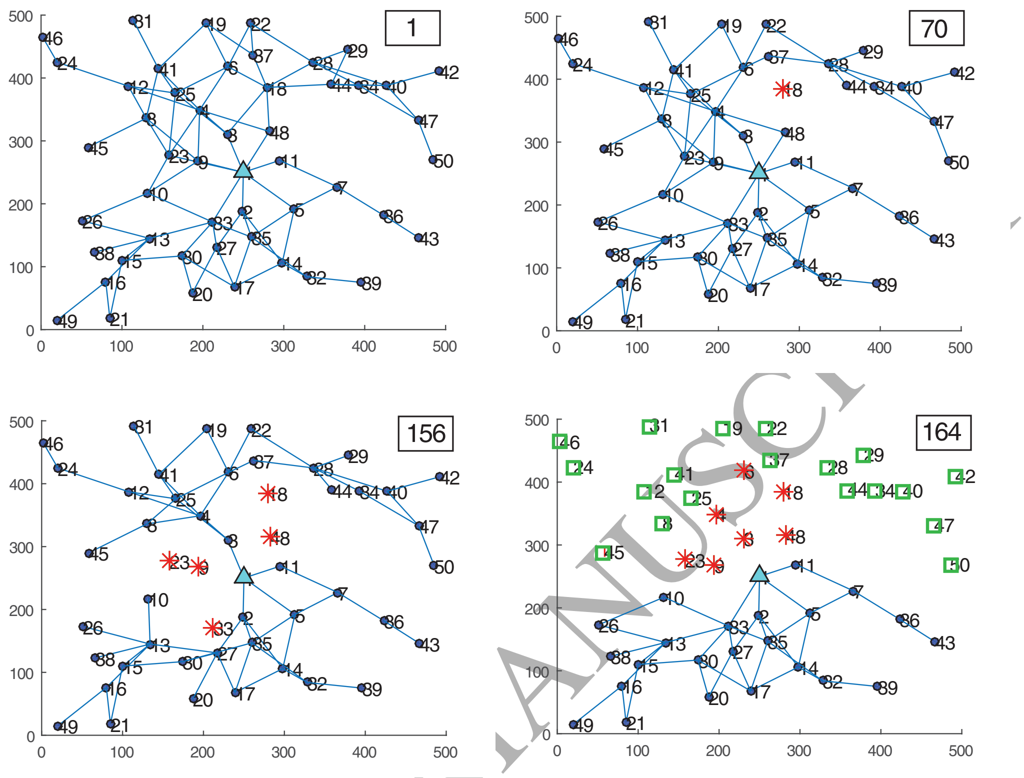

Figure 3: Network connectivity during the network lifetime

3.1. System Model

We assume that perpetually-powered FC is placed at the center of the network and a set $\mathcal{N}$ of N energy-harvesting sensors (EHSs) are randomly distributed in a two-dimensional network. A simple beacon-based MAC protocol is assumed in this paper for medium access.

We consider that each node $i \in \mathcal{N}$ generates and transmits their event reports periodically to a fusion center at the rate of λ events per second over a time-varying wireless channel. Each cycle that nodes sense and transmit is considered a round. These packets are routed through the network and are forwarded to the FC in a greedy manner. In a greedy forwarding, each node forwards the message to the neighbor that is closer to the FC based on only local information. Thus, in this network, each node forwards the packet to the neighbor which has a lower distance (hop-count) to the FC. Therefore, each node (except nodes on the outskirts of the network) works as a relay for its neighboring sensor nodes. Thus, total traffic that node i transmits at each round, tr_i^t, is the summation of the traffic it relays, tr_i^r, and the sensing traffic it generates, tr_i^s. We have then

$$tr_i^s = \frac{1}{s_i}, \quad [packet/second], \tag{1}$$

where s_i is the sensing period of node i. Nodes consider one-hop neighbors, those nodes that are within a transmission range of each other at the default energy level.

After network deployment, each node is aware of its upstream and downstream neighboring nodes. In each round, nodes send their packets towards the fusion center using downstream nodes. Each node might have more than one downstream neighbor. Thus, each node selects the forwarder node using the probability expressed in Eq. (2). For example, if a node has 3 downstream nodes, the probability of selecting each node is 1/3. Let $\mathcal{D}_i$ be the set of potential forwarding nodes for node i, i.e., downstream nodes for node i, define also $n_i = \mid \mathcal{D}_i \mid$ as the cardinality of set $\mathcal{D}_i$, and t_i as the beacon period of node i, then the probability that node i forwards the traffic to node j is defined as

$$p_{i,j} = \frac{1}{t_i \sum_{a \in \mathcal{D}_i} \frac{1}{t_a}}, \tag{2}$$

If we consider all the nodes having the same beacon period, the probability can be simply expressed as $p_{i,j} = \frac{1}{n_i}$.

Let $\mathcal{U}_i$ be the set of nodes for which node i is a potential forwarding node, i.e., upstream nodes for node i. Define $m_i = \mid \mathcal{U}_i \mid$ as cardinality of the set $\mathcal{U}_i$. Thus, the total traffic transmitted by sensor node i is given by tr_i^t, which is obtained as follows

$$tr_i^r = \sum_{k \in \mathcal{U}_i} p_{k,i} tr_k^t,$$

$$tr_i^t = tr_i^s + tr_i^r = \frac{1}{s_i} + \sum_{k \in \mathcal{U}_i} p_{k,i} tr_k^t.$$

3.2. Packet Delivery and Outage Model

If the packet does not reach the FC, the packet is dropped, and a measurement outage occurs. Outage might occur due to channel conditions, or shortage of remaining energy at a node, or disconnected link. It is assumed that nodes are location-aware (e.g., equipped with GPS, or sensors have localization information available) and can communicate with neighbors in the coverage region. We refer to the coverage region of a sensor as a circular region centered on it, whose radius is determined by the transmission power and the path loss model. The path loss is modeled as a log-distance path loss model, [26]. Defining $P_{T_{dB}}$ as the transmission power in dB, n as the path loss exponent, and $\overline{P_{R_{dB}}(d)}$ as the average received power in dB at separation distance d, we have

$$\overline{P_{R_{dB}}(d)} = P_{T_{dB}} - 10n\log_{10}(d). \tag{3}$$

Assuming that the path loss follows a normal distribution in dB, we can write the above equation as

$$P_{R_{dB}}(d) = P_{T_{dB}} - 10n\log_{10}(d) + X_\sigma, \tag{4}$$

where, $X_\sigma \sim \mathcal{N}(0, \sigma)$ is a Gaussian random variable with zero mean and standard deviation σ in dB. Thus, $P_{R_{dB}}(d)$ is also Gaussian distributed, and we can see that

$$P_{R_{dB}}(d) \sim \mathcal{N}\left(P_{T_{dB}} - 10n\log_{10}(d), \sigma\right). \tag{5}$$

In order for the received signal to be readable at the receiver, the received power should be higher than the receiver sensitivity, γ_{dB}. Therefore, as $P_{R_{dB}}(d)$ is Gaussian distributed, to calculate the probability of a successful received signal $P\left(P_{R_{dB}}(d) > \gamma_{dB}\right)$, we use the Q-function to calculate the tail probability of the standard normal distribution, [26]. Thus, we have

$$P\left(P_{R_{dB}}(d) > \gamma_{dB}\right) = Q\left(\frac{\gamma_{dB} - (P_{T_{dB}} - 10n\log_{10}(d))}{\sigma}\right). \tag{6}$$

To demonstrate and model the effect of multiple packet collisions, we define the neighbor density for node i, μ_i, as follows

$$\mu_i = \frac{N_i \pi r^2}{A}, \tag{7}$$

where N_i is the total number of neighbors that node i has, r is the transmission range of node i and A is the area covered by node i. Then the neighbor density parameter μ_i of node i, is associated with the noise floor F (the sum of all the unwanted signals produced by other sources), in such a way that the more neighboring nodes a sensor has, the higher the noise floor is, hence decreasing the probability of a successful delivery of a packet. Thus, the final probability of packet delivery is calculated as

$$P\left(P_{R_{dB}}(d) > \gamma_{dB}\right) = Q\left(\frac{(\gamma_{dB} + F) - (P_{T_{dB}} - 10n\log_{10}(d))}{\sigma}\right). \tag{8}$$

.

As the probability of successful reception of a packet is a function of distance and distances are different, thus, the probability in (8) can vary for each node in the next hop. For each packet generated by each node, it will be delivered to the next hop with a probability of $P\left(P_{R_{dB}}(d) > \gamma_{dB}\right)$ at each round.

It is assumed that each node is equipped with a supercapacitor with negligible storage inefficiency to store its harvested energy. Supercapacitor helps the EHSs to partially overcome the randomness in the energy harvested.

3.3. Energy Harvesting Model

For energy harvesting, there are several models that are considered such as the leaky-bucket model [11], the Markov model [27], the Bernoulli model [28], etc. In this paper, solar powered sensors are considered, the amount of harvested energy depends on the light intensity at each physical location. For example, consider some solar powered sensors distributed randomly in a field. It is reasonable to consider the nodes in the same vicinity to have light with the same intensity. Thus, nodes harvest with different probability, depending on the environment they are operating in, as depicted in Figure 4, where E_x^t represents the nodes' energy level at time t, $E_{h_x^t}$ represents the node harvesting rate at time t and Γ_x^t represents the power consumption at time t. Therefore, to emulate this effect, the network is divided into different regions and at each region, nodes harvest with the same probability η_i (see Figure 5). The effect of random harvested energy is expressed as follows

$$E_h = \eta_i \times E_{\max}, \tag{9}$$

where η_i is the probability of harvesting energy in region i, which is a uniformly distributed random number between [0.5, 1]. E_{max} is the harvested energy corresponding to the highest light intensity. The η_i value 0.5 is considered to mimic a partially clouded area where nodes in that region can harvest with half the value of E_{max}, and $\eta_i = 1$ represents a clear sky where nodes can harvest energy with the highest ratio.

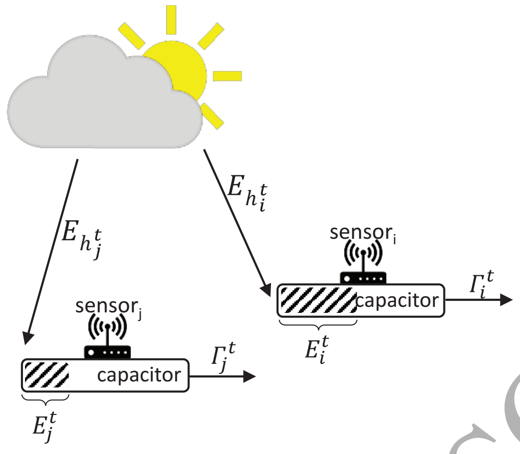

Figure 4: Energy harvesting model for two different nodes in different location

η_1	η_2	η_3	η_4
η_5	η_6	η_7	η_8
η_9	η_{10}	η_{11}	η_{12}
η_{13}	η_{14}	η_{15}	η_{16}

Figure 5: Harvesting power probability map

Recall that $\mathcal{N}$ is the set of sensor nodes distributed in the network, then the node residual power (NRP) of each node i, $i \in \mathcal{N}$ is calculated as

$$NRP_i^{t+1} = \left\{ \frac{(E_i^t - \Gamma_i^t) + E_{h_i^j}}{t}, C_{\max} \right\} \tag{10}$$

where t is the beacon duration, and C_{max} is the maximum power capacity that a node capacitor can have. NRP is quantized into three levels: stable, medium, and critical which are defined as

$$NRP_{state} = \left\{ \begin{array}{l} stable \stackrel{\text{def}}{=} NRP \geq \alpha \\ medium \stackrel{\text{def}}{=} \beta \leq NRP < \alpha \\ critical \stackrel{\text{def}}{=} \gamma \leq NRP < \beta \end{array} \right\} \tag{11}$$

where power parameters α, β, and γ are tunable parameters that can be modified based on the application or network requirements for a better performance. With the definition of these three levels, we can define which nodes can increase transmission power and which nodes need to operate with default transmission power. A node increases its transmission power if it has neighboring downstream nodes in the critical status and if its own status is stable.

3.4. Protocol description

In our routing protocol, each node locally maintains a one-hop neighbor list and their locations, where one-hop neighbors are those sensors that are within a transmission range of each other at the default power level. Each node announces its distance to the FC in a beacon packet and nodes forward their information and relay data opportunistically to a neighbor that has lower hop-count to the FC. Instead of waiting for a specific receiver, based on the arrival beacon, a sender forwards its data to a sensor with lower hop-count towards the FC. Once a node energy drops below certain threshold γ, the node requests its neighbors to increase their transmission power. The nodes that receive this request check their energy level, and based on the amount of available energy that they have, they decide to increase their transmission power or continue at the current mode. Using this method, nodes that are farther from the FC can reach it in less hops, and low energy nodes can be excluded from handling heavy traffic. Consider a network illustrated in Figure 6(a). Each node is sending the data to its neighbor with lower hop-count towards the FC. As it can be seen, node d is the bottleneck of the network. Once node d runs out of power (Figure 6(b)), nodes a, b and c get disconnected from the rest of the network, which is a normal situation in most of the EH-WSNs routing protocols. In ADTPC, once node d goes under certain critical energy level, it will announce to its neighbors to increase their transmission power, which eventually results in longer effective transmission range. As it is illustrated in Figure 6(c), nodes a and c increase power and now they can reach nodes e and f, respectively. Therefore, there would be lower traffic load on node d and it can still be part of the network and operate normally, while harvesting energy.

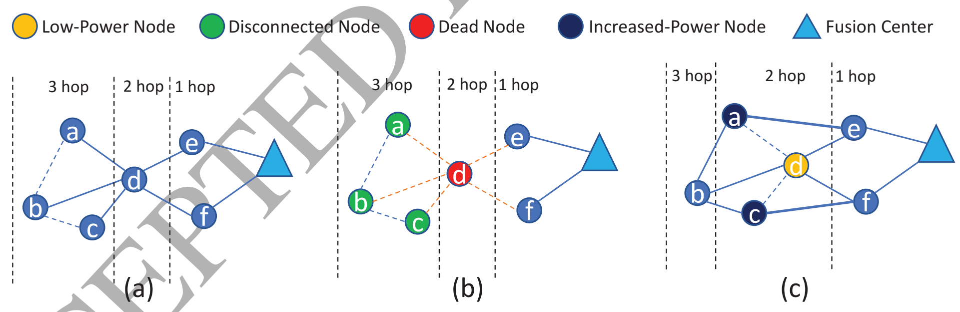

Figure 6: Comparison of different network status for (a) normal network operation, (b) disconnected network, and (c) ADTPC method

However, increasing the transmission power to reach farther comes with a cost. To increase the transmission range nodes must increase transmission power and consume more energy than in the normal operation mode. Thus, ADTPC forces nodes to go back to their normal transmission power once their energy level falls under certain threshold. It needs to be highlighted that nodes are harvesting energy constantly and their energy level changes frequently during the network lifetime.

ADTPC pseudocode is presented in Algorithm 1. Nodes start by listening for beacon packets from neighbors, Ngh_i for sensor i. Once the beacon packet is received, the node checks the flag for changing transmission power, $ChTP$. If the flag is active and NRP_i is greater than α, it increases its transmission power to δ. If node is in medium power condition $\beta \leq NRP_i < \alpha$, it increases its power to θ ($\theta < \delta$). However, if node i is in low power condition $\gamma \leq NRP_i < \beta$, it does not change its transmission power and it operates with the default transmission power. The power parameters, $\alpha, \beta, \gamma, \delta$ and θ are tunable parameters that can be modified based on the application or network requirements for better performance.

Algorithm 1: Routing pseudocode

```
input : N: Set of network nodes
        n_i: Node i ∈ N
        Ngh_i: Neighbor list of node i
        ChTP: Flag for changing transmission Power
        NRP_i: Node i residual power
        α, β, γ: Power level parameters
        δ, θ: Power control parameters
1  begin
2      ∀n_i ∈ N;
3      n_i listens for beacon;
4      if n_i receives beacon from n_j, where n_j ∈ Ngh_i && ChTP = 1 then
5          n_i checks NRP_i;
6          if α ≤ NRP_i then
7              n_i increase transmission power to δ;
8          else if β ≤ NRP_i < α then
9              n_i increase transmission power to θ;
10         else if γ ≤ NRP_i < β then
11             n_i operates on default transmission power;
12         end
13     end
14     if NRP_i < γ then
15         ChTP = 1;
16         broadcast beacon;
17     end
18     goto Line 2;
19 end
```

4. Performance Evaluation

In this section, the performance of the proposed protocol is studied using numerical evaluation in MATLAB. Several performance metrics such as packet delivery ratio (PDR), end-to-end delay, and power consumption are studied. Also, network behavior is analyzed under several conditions. The performance of the proposed algorithm is compared with the normal greedy forwarding and the simple dynamic duty cycle (DDC) protocols. We consider initially a 1000 m × 1000 m network environment in which a total of 100 nodes are deployed randomly. We assume that each node is aware of its location and the distance (hop-count) to the FC. Nodes broadcast

Table 1: Simulation parameters

Number of nodes	100, 200
Network size	1000 m × 1000 m
Distribution	Random
Transmission range	Default=100, θ=150, δ=200 meters
Power parameters	α=50%, β=25%, γ=10%
Capacitor	300 energy units
Sensing rate	1 event per 30 second
Energy harvesting rate	6 units per round
Consumption rate	1,3,10 units per round depending on transmission power
Event rate	1 unit per round per node
Noise Floor	0, 10, 20, 30, 40 dB
Simulation run	50 rounds
Confidence interval	90%

their hop-count distance to the FC and their available power through the beacon packet. Each node produces an event in each 30 second interval. The event can be considered as a local measurement of some parameters from the environment such as temperature, humidity, vibration, etc. The nodes forward the measurement data to the FC. For the transmission of one event (transmitting its measurement or relaying the neighbors' data) each node uses 1 unit of power, while harvesting 6 units of power in each round. We assume each node is equipped with a supercapacitor such as 3FNESSCAP [29], for energy storage for harvested energy. At the initial stage, the supercapacitor is considered fully charged and it can hold up enough power for 300 events. Results shown are the average of 50 runs with different network setups and 90% confidence intervals. General simulation parameters are summarized in Table 1.

Figure 7 illustrates the number of inactive nodes in the network against number of rounds. Recall that a node becomes inactive when it runs out of energy. As it can be observed from the results, DDC and greedy forwarding show slightly similar performance in the network with 100 nodes (16% inactive nodes), while ADTPC protocol shows the lowest number of inactive nodes (8%) in the network. The three protocols initiate with similar performance (up to round 10), and then ADTPC balances the traffic with increasing transmission power to avoid the creation of bottleneck nodes and their eventual inactive state by consumption of energy. By increasing the number of sensor nodes to 200, ADTPC shows a sharp increase in first 50 rounds, and later the network converges to a stable state with an average of 17% of inactive nodes. The reason behind the sharp increase is that several nodes increase their transmission range and consume more power before the network reaches stable state. Meanwhile, DDC shows the highest inactive ratio with 25%, and the greedy forwarding shows 22% average of inactive nodes in the network. As most of the network traffic is forwarded through the nodes closer to the FC, those nodes die faster in greedy forwarding. In DDC, those nodes may still have energy, but DDC forces them to sleep and not to participate in transmissions, which eventually makes them inactive occasionally. However, in the proposed method, when the nodes find out about low energy neighbors, they increase transmission power to reach farther in the network, and indirectly reduce the traffic load on the low energy nodes.

Once the nodes closer to the FC run out of energy, in some cases, it results in several nodes being disconnected from the rest of the network. The effect of disconnected nodes is depicted

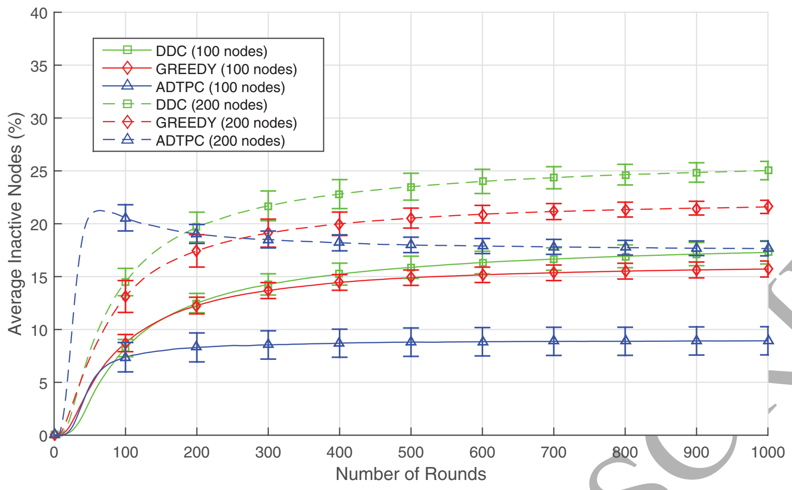

Figure 7: Average number of inactive node in the network

in Figure 8 for a network with 100 and 200 nodes. As it can be seen, the high percentage of inactive nodes in DDC and greedy protocols leads to high percentage of disconnected nodes. It is shown that on average, DDC and greedy forwarding have 20% of the nodes disconnected from the network in each round. On the other hand, in ADTPC, the network stays connected most of the time and there is noticeably a lower number of disconnected nodes compared to that of the other methods. However, by increasing the number of nodes from 100 to 200, DDC and greedy forwarding show lower disconnected node ratio due to higher number of nodes around the FC and more possible routes. Meanwhile, ADTPC achieves the same result as with 100 nodes, and outperforms the existing approaches. It is needed to be highlighted that, in the proposed method due to the dynamic transmission power management that results in indirect load balancing, the inactive nodes are not always the nodes that are near the FC. Thus, most of the time, nodes do not get fully disconnected from the network.

Performance of the protocols in terms of PDR is shown in Figure 9. As it is explained in the previous results, ADTPC keeps the network connected by trying to distribute the traffic load on the network and by avoiding the creation of inactive nodes around the FC. This results in higher PDR as it is shown in this result. As it can be observed from the figure, DDC and greedy forwarding are showing slightly similar performance in a network with 100 nodes and they converge to 45 percent PDR, while ADTPC reaches steady state and achieves 65% of PDR. During the first 100 rounds, the PDR degrades for all the protocols, but ADTPC shows the lowest degradation ratio compared to other protocols. By increasing the nodes in the network to 200, all the protocols show the same pattern and still the ADTPC can achieve twice as much PDR compared to existing approaches. It needs to be mentioned that in the proposed protocol, due to increasing transmission power and eventually more interference in the network, in first 50 rounds it shows slightly lower PDR compared to the other methods. However, the proposed method reaches steady state faster than other protocols and shows higher PDR.

Figure 10 depicts the result of the average end-to-end delay in the network. As it can be seen, by running the network for several rounds, delay slightly increases for all the protocols because some nodes are out of the operation and initial routes are not available. However, ADTPC

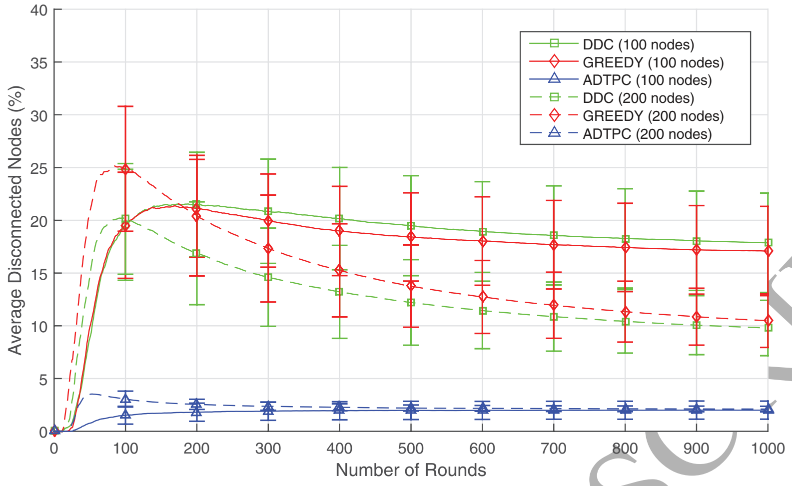

Figure 8: Average number of disconnected nodes in the network

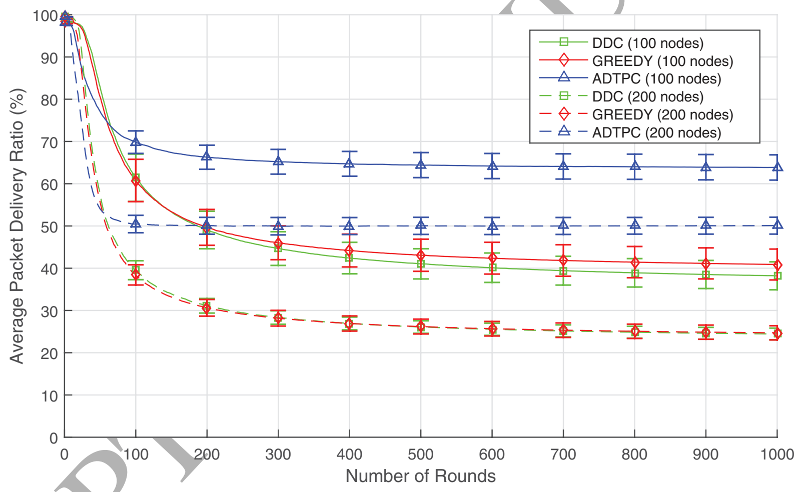

Figure 9: Average packet delivery ratio

outperforms DDC and greedy forwarding in both 100 and 200 nodes, and shows lower delay due to delivering the packet to the FC in a lower hop count (see Figure 11). On the other hand, in some cases for DDC and greedy forwarding, the number of hop-count increases sharply due to several inactive nodes around the FC, which results in inefficient and less possible routes.

In the remaining of the section, DDC results are omitted as they follow the behavior of the greedy forwarding algorithm. The average path length in each round is illustrated in Figure 11. As it can be seen, when 100 nodes are deployed in the network, greedy routing delivers the packet to the FC in an average of 6 hops, while the value is 4 for ADTPC. It is because of changing transmission power and consequently transmission range in ADTPC, where nodes can reach farther in the network and deliver the packets using less hops. By increasing the network

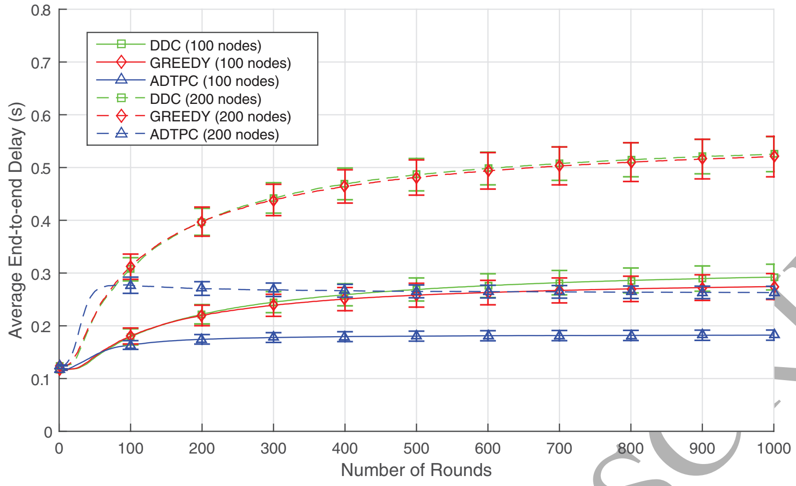

Figure 10: Average packet end-to-end delay

density (200 nodes), ADTPC shows a slight increase to an average of 5 hops, while the greedy shows a sharp increase to an average of 8 hops. It needs to be noted that having a higher number of nodes in the network, creates more possible routes and consequently higher average hop-count to the FC.

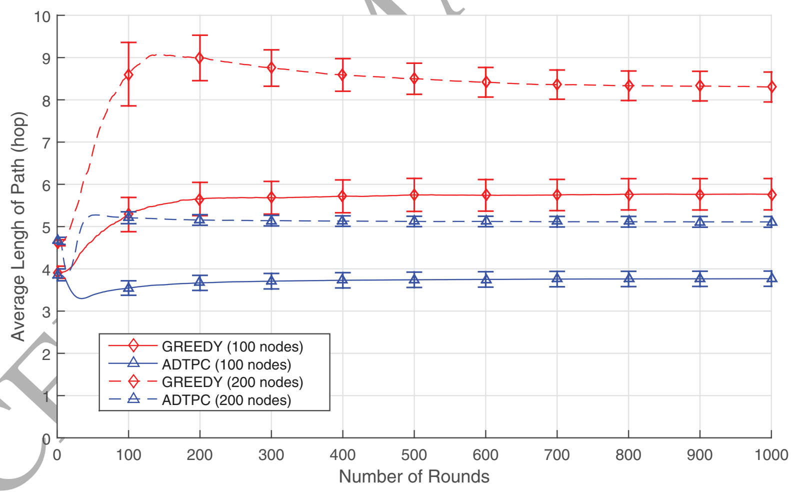

Figure 11: Average path length at each round

Figure 12 illustrates the average residual energy at each round. As it can be observed, ADTPC uses more energy on average due to distributing the traffic as well as increasing transmission power. It can be seen, that the average remaining energy converges to a steady state of 37% and 30% of initial power for 100 nodes and 200 nodes, respectively. However, in greedy forwarding, the average remaining energy reaches steady state of 70% and 60% for 100 nodes and 200 nodes, respectively. The reason is that in greedy forwarding the power management is not considered and some nodes run out of energy while some nodes have a full capacitor, but will not be connected. While, ADTPC tries to balance power and traffic at the same time.

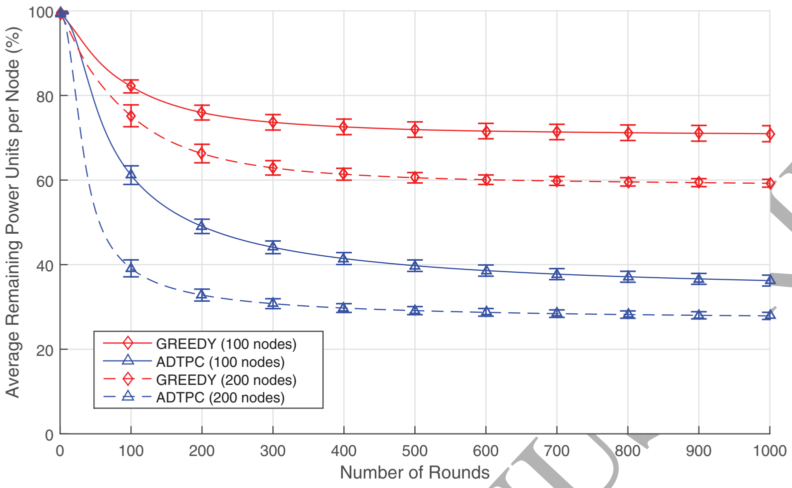

Figure 12: Average remaining energy units per node at each round

The average energy consumed for each successful packet is depicted in Figure 13. As it can be seen, when 100 nodes are deployed in the network, ADTPC uses around one more unit of energy compared to the greedy algorithm. However, by increasing the number of nodes, it can be seen after 400 rounds, ADTPC reaches stable condition and shows lower value compared to that of the greedy forwarding. This is due to having a higher node density and multiple route options, which eventually make the nodes less likely to increase their transmission power. It can be concluded that although ADTPC uses higher average energy per node, it has a higher packet delivery ratio. In other words, it uses the harvested energy more rigorously in order to improve network end-to-end performance such as PDR and delay.

5. Network Topology Behavior

We have seen with the results in the previous section, that the ADTPC algorithm performs better than the greedy algorithm. One of the reasons is that when the sensors use adaptively different transmission power ranges, the network increases connectivity of the sensors. Recall that the transmission range of a sensor is adjusted when neighbors have critical energy levels, thus using other sensors to transmit information to the fusion center. This action also helps those sensors in critical energy levels to recover by the energy harvesting process. When energy levels are back up to normal, then the transmission range is adjusted back again to the default transmission power.

In order to visualize this, we carry out a statistical analysis of the network. During the simulation, we generated for each round m an indicator random variable X_m as follows

$$X_m = \begin{cases} 1, & \textit{at least a sensor is disconnected}, \\ 0, & \textit{otherwise}. \end{cases} \quad (12)$$

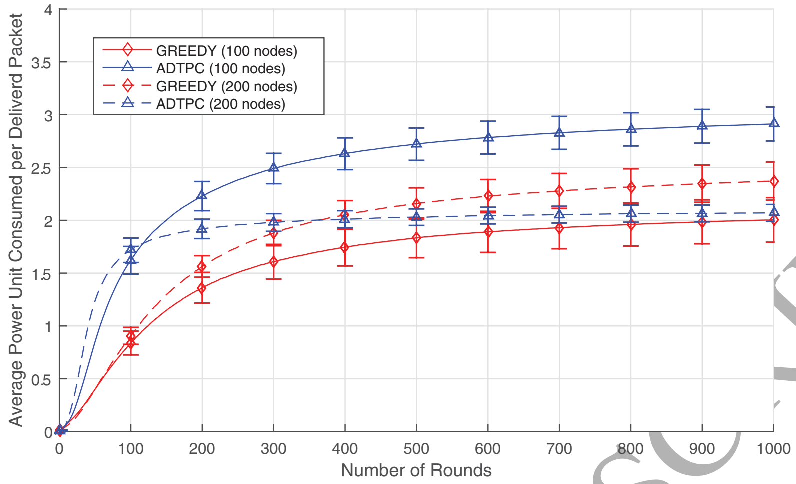

Figure 13: Average energy units consumed per delivered packet at each round

We can see that $\{X_m, m \geq 0\}$ is a stochastic process indicating those rounds where at least one sensor in the network is disconnected, and hence unable to transmit its information to the FC. This event occurs when a sensor becomes inactive due to the lack of energy and such sensor is a relay of other sensors, and then these sensors will be unable to transmit their information. One can see that the adjustment of the transmission range in the ADTPC technique would be able to connect some of those sensors that were using such relay sensor. Also, $\{X_m, m \geq 0\}$ can be considered as an on/off process as shown in Figure 14.

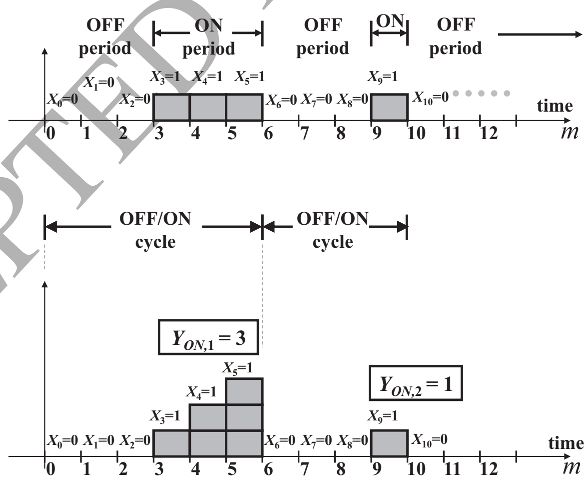

Figure 14: Stochastic On/Off process of disconnected states of the network.

We are interested in the duration of the on periods in the $\{X_m, m \geq 0\}$ process, because it represents the duration of time that a component of the network topology (group of sensors) is disconnected and kept from transmitting information to the fusion center. So we perform the counting for the duration of the on periods (disconnected state) and generate the process $\{Y_{ON,k}, k \geq 1\}$ as shown in the same Figure 14. We simulated different network setups for 10,000 rounds. Once we have the process $\{Y_{ON,k}, k \geq 1\}$, we obtain its statistics for both scenarios in the network (the greedy and ADTPC algorithms).

First, we see if some known distribution can represent the behavior of the disconnected state of the network. To do this, we obtain pp-plots comparing the data obtained from the simulation to a Weibull distribution and to an exponential distribution, these are shown in Figure 15. The Weibull distribution that was considered has a probability density function (pdf) with two parameters given by [30]

$$f_Y(y) = \frac{\eta}{\omega^\eta} y^{\eta-1} e^{-(\frac{y}{\omega})^\eta}, \quad y > 0. \tag{13}$$

Parameters $\omega > 0$ (scale parameter) and $\eta > 0$ (shape parameter) were obtained for both, the greedy and the ADTPC algorithms. In both cases, parameter η was close to one, i.e., 1.10 for the greedy, and 1.17 for the ADTPC algorithm. With a unitary value of η, the Weibull distribution becomes the exponential distribution with parameter $1/\omega$. Thus, data will fit better to an exponential distribution. From figures 15(a) - (d), we can see that for both (greedy and ADTPC algorithms), the fit is better for the exponential distribution (figures 15(c) and (d)) than for the Weibull distribution.

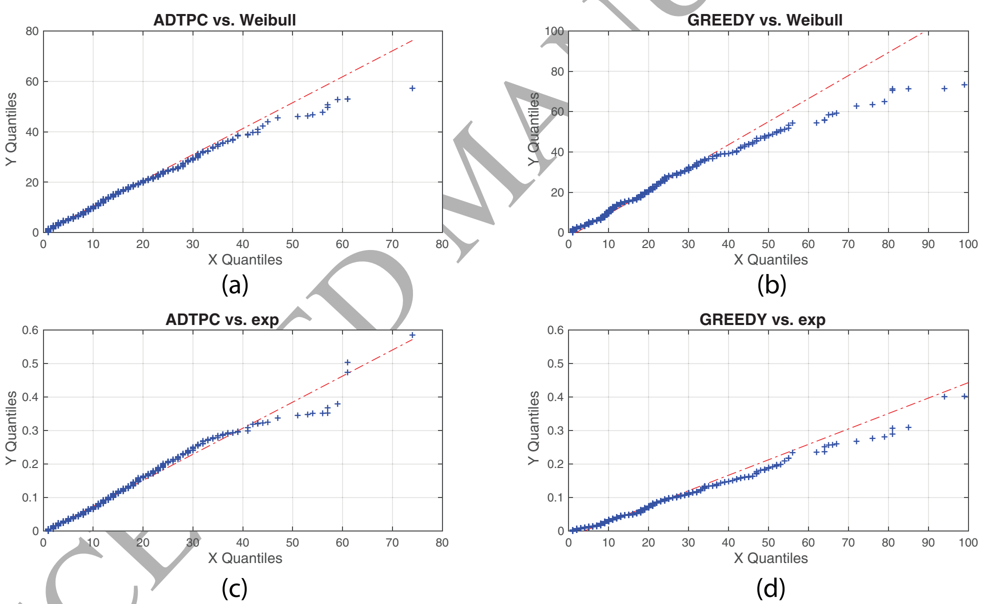

Figure 15: pp-plots for the duration of the disconnected states of the network.

Once we have a description of the statistical behavior, we proceed to obtain the cumulative distribution function (cdf) and the corresponding probability density function (pdf). Figure 16 shows the complementary cdf (ccdf), the histograms and the pdfs for both algorithms. We can see the close match for the exponential distribution for the ccdf and that the exponential pdf closely resembles the histograms of both algorithms.

In Figure 16(a), we can see that the ADTPC has a smaller proportion of time in disconnected states of the network and that those disconnected states have durations that are also smaller than

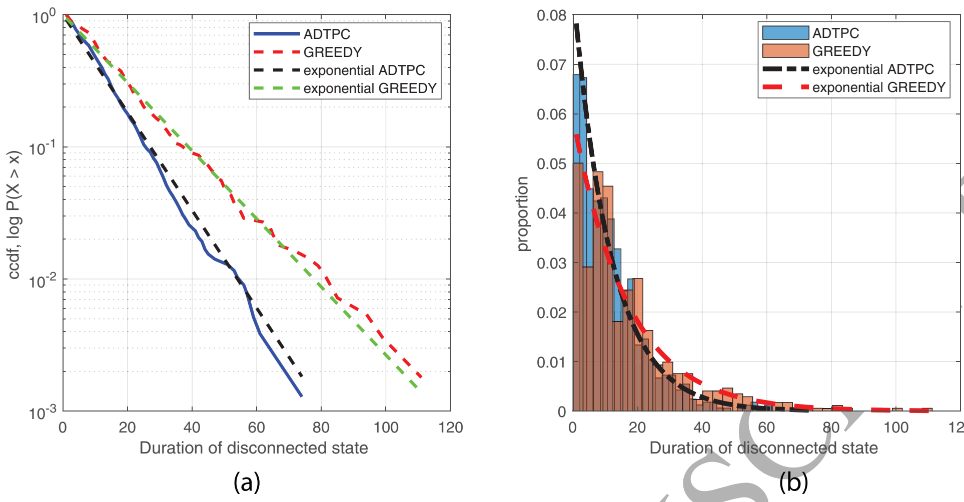

Figure 16: ccdfs, histograms and pdfs for process $\{Y_{ON,k}, k \geq 1\}$.

those for the greedy algorithm. This can also be seen in the pdf of Figure 16(b) because the tail of the pdf for the greedy algorithm is heavier than that for the ADTPC, thus resulting in higher probabilities of having longer periods of disconnected states for the greedy algorithm. This is also evident when the index of dispersion (variance / mean) is calculated for the simulation data obtained in the process $\{Y_{ON,k}, k \geq 1\}$, resulting for the greedy algorithm in an index of dispersion of $\rho = 258.0448/16.8651 = 16.0638$, whereas for ADTPC we have $\rho = 110.3442/11.7352 = 10.5045$, which represents the effects of the adjustment of transmission range on connectivity in the network.

This brief statistical analysis of the topology behavior is part of the reason why the proposed algorithm outperforms the greedy algorithm.

6. Conclusion

This paper proposed a new routing protocol for energy-harvesting sensor network by exploiting the benefits of changing the transmission power dynamically. Based on the local information of the neighboring nodes' energy, each node independently decides about dynamically changing its transmission power for communication. Once the nodes are in critical power condition, they announce their power level to the neighbors and neighboring nodes decide to increase their transmission power based on their residual power condition. Using this method, traffic load on the low power node decreases and consequently it results in load balancing in the network and an increase of connected sensors. Simulation results indicate that the proposed protocol outperforms existing protocols and achieves better end-to-end network performance. We also introduced a statistical description of the connectivity of the network to explain the performance improvement of the proposed protocol. For route selection, in this paper we followed the greedy forwarding scheme. However, in the future other network and link parameters such as link quality, density, energy harvesting and consumption rate are going to be considered for route selection, which we believe leads to improvement in the performance metrics.

Acknowledgment

This work was supported by the SEP-CONACyT Research Project 255387, the School of Engineering and Sciences and the Telecommunications Research Focus Group at Tecnologico de Monterrey.

References

[1] R. H. Weber, R. Weber, Internet of things, Vol. 12, Springer, 2010.
[2] M. S. Hossain, G. Muhammad, Cloud-assisted industrial internet of things (iiot)–enabled framework for health monitoring, Computer Networks 101 (2016) 192–202.
[3] J. A. Guerrero-ibanez, S. Zeadally, J. Contreras-Castillo, Integration challenges of intelligent transportation systems with connected vehicle, cloud computing, and internet of things technologies, IEEE Wireless Communications 22 (6) (2015) 122–128.
[4] S. Balampanis, S. Sotiriadis, E. G. Petrakis, Internet of things architecture for enhanced living environments, IEEE Cloud Computing 3 (6) (2016) 28–34.
[5] B. Hafidh, H. Al Osman, J. S. Arteaga-Falconi, H. Dong, A. El Saddik, Site: The simple internet of things enabler for smart homes, IEEE Access 5 (2017) 2034–2049.
[6] F. K. Shaikh, S. Zeadally, Energy harvesting in wireless sensor networks: A comprehensive review, Renewable and Sustainable Energy Reviews 55 (2016) 1041–1054.
[7] F. Akhtar, M. H. Rehmani, Energy replenishment using renewable and traditional energy resources for sustainable wireless sensor networks: A review, Renewable and Sustainable Energy Reviews 45 (Supplement C) (2015) 769 – 784.
[8] A. A. Babayo, M. H. Anisi, I. Ali, A review on energy management schemes in energy harvesting wireless sensor networks, Renewable and Sustainable Energy Reviews 76 (2017) 1176–1184.
[9] Z. Han, J. Wu, J. Zhang, L. Liu, K. Tian, A general self-organized tree-based energy-balance routing protocol for wireless sensor network, IEEE Transactions on Nuclear Science 61 (2) (2014) 732–740.
[10] J.-B. Seo, On minimizing energy consumption of duty-cycled wireless sensors, IEEE Communications Letters 19 (10) (2015) 1698–1701.
[11] A. Kansal, J. Hsu, S. Zahedi, M. B. Srivastava, Power management in energy harvesting sensor networks, ACM Transactions on Embedded Computing Systems (TECS) 6 (4) (2007) 32.
[12] M. H. Anisi, G. Abdul-Salaam, M. Y. I. Idris, A. W. A. Wahab, I. Ahmedy, Energy harvesting and battery power based routing in wireless sensor networks, Wireless Networks 23 (1) (2017) 249–266.
[13] T. Voigt, H. Ritter, J. Schiller, Solar-aware routing in wireless sensor networks, in: IFIP International Conference on Personal Wireless Communications, Springer, 2003, pp. 847–852.
[14] L. Lin, N. B. Shroff, R. Srikant, Asymptotically optimal energy-aware routing for multihop wireless networks with renewable energy sources, IEEE/ACM Transactions on networking 15 (5) (2007) 1021–1034.
[15] E. Lattanzi, E. Regini, A. Acquaviva, A. Bogliolo, Energetic sustainability of routing algorithms for energy-harvesting wireless sensor networks, Computer Communications 30 (14) (2007) 2976–2986.
[16] T. Voigt, A. Dunkels, J. Alonso, H. Ritter, J. Schiller, Solar-aware clustering in wireless sensor networks, in: Proceedings. ISCC 2004. Ninth International Symposium on Computers And Communications, Vol. 1, 2004, pp. 238–243.
[17] K. Zeng, K. Ren, W. Lou, P. J. Moran, Energy aware efficient geographic routing in lossy wireless sensor networks with environmental energy supply, Wireless Networks 15 (1) (2009) 39–51.
[18] Z. A. Eu, H.-P. Tan, W. K. Seah, Routing and relay node placement in wireless sensor networks powered by ambient energy harvesting, in: Wireless Communications and Networking Conference, 2009. WCNC 2009. IEEE, IEEE, 2009, pp. 1–6.
[19] Y. Cao, X.-Y. Liu, L. Kong, M.-Y. Wu, M. K. Khan, Ehr: Routing protocol for energy harvesting wireless sensor networks, in: Parallel and Distributed Systems (ICPADS), 2016 IEEE 22nd International Conference on, IEEE, 2016, pp. 56–63.
[20] C. Tang, Q. Tan, Y. Han, W. An, H. Li, H. Tang, An energy harvesting aware routing algorithm for hierarchical clustering wireless sensor networks., KSII Transactions on Internet & Information Systems 10 (2) (2016) 504–521.
[21] Y. Dong, J. Wang, B. Shim, D. I. Kim, Dearer: A distance-and-energy-aware routing with energy reservation for energy harvesting wireless sensor networks, IEEE Journal on Selected Areas in Communications 34 (12) (2016) 3798–3813.
[22] X. Fafoutis, N. Dragoni, Analytical comparison of mac schemes for energy harvestingwireless sensor networks, in: Networked Sensing Systems (INSS), 2012 Ninth International Conference on, IEEE, 2012, pp. 1–6.

[23] Z. A. Eu, H.-P. Tan, Probabilistic polling for multi-hop energy harvesting wireless sensor networks, in: Communications (ICC), 2012 IEEE International Conference on, IEEE, 2012, pp. 271–275.

[24] J. Kim, J.-W. Lee, Energy adaptive mac protocol for wireless sensor networks with rf energy transfer, in: Ubiquitous and Future Networks (ICUFN), 2011 Third International Conference on, IEEE, 2011, pp. 89–94.

[25] X. Fafoutis, N. Dragoni, Odmac: an on-demand mac protocol for energy harvesting-wireless sensor networks, in: Proceedings of the 8th ACM Symposium on Performance evaluation of wireless ad hoc, sensor, and ubiquitous networks, ACM, 2011, pp. 49–56.

[26] T. S. Rappaport, et al., Wireless communications: principles and practice, Vol. 2, Prentice Hall PTR New Jersey, 1996.

[27] V. Sharma, U. Mukherji, V. Joseph, S. Gupta, Optimal energy management policies for energy harvesting sensor nodes, IEEE Transactions on Wireless Communications 9 (4) (2010) 1326–1336. doi:10.1109/TWC.2010.04.080749.

[28] A. Erturk, D. J. Inman, An experimentally validated bimorph cantilever model for piezoelectric energy harvesting from base excitations, Smart Materials and Structures 18 (2) (2009) 025009.

[29] NESSCAP Inc., Nesscap ultracapacitor products,; available from: www.nesscap.com.

[30] K. V. Bury, Statistical Distribution in Engineering, Cambridge University Press, Cambridge, MA., 1999.

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