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Enhancing the Performance of Energy Harvesting Sensor Networks for Environmental Monitoring Applications

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Abstract: Fast development in hardware miniaturization and massive production of sensors make them cost efficient and vastly available to be used in various applications in our daily life more specially in environment monitoring applications. However, energy consumption is still one of the barriers slowing down the development of several applications. Slow development in battery technology, makes energy harvesting (EH) as a prime candidate to eliminate the sensor's energy barrier. EH sensors can be the solution to enabling future applications that would be extremely costly using conventional battery-powered sensors. In this paper, we analyze the performance improvement and evaluation of EH sensors in various situations. A network model is developed to allow us to examine different scenarios. We borrow a clustering concept, as a proven method to improve energy efficiency in conventional sensor network and brought it to EH sensor networks to study its effect on the performance of the network in different scenarios. Moreover, a dynamic and distributed transmission power management for sensors is proposed and evaluated in both networks, with and without clustering, to study the effect of power balancing on the network end-to-end performance. The simulation results indicate that, by using clustering and transmission power adjustment, the power consumption can be distributed in the network more efficiently, which result in improving the network performance in terms of a packet delivery ratio by 20%, 10% higher network lifetime by having more alive nodes and also achieving lower delay by reducing the hop-count.

Keywords: energy harvesting; wireless sensor network; environmental monitoring; clustering; energy efficiency; network lifetime; transmission power

1. Introduction

The increasing demand of smartness in our daily appliance and novel applications for more efficient use of the resources have led to a massive boom in the deployment of sensors. Due to technological advances, sensors are getting smaller and more powerful. However, the efficient managing of the small energy resource of the sensor is still a challenging task. Therefore, there have been several energy efficient algorithms and protocols proposed and put in experiments in many research papers and practical applications [1–4]. Apart from focusing on the efficient use of the limited power resource, harvesting energy from the ambient environment can be a promising solution for the aforementioned challenge. Energy harvesting cannot only extend the network lifetime in a sustainable manner, but it can also reduce the necessity of using batteries that pollute the environment due to leakage or when they are discarded [5].

While energy harvesting (EH) is not a new research topic, it has recently attracted more attention due to the massive implementation of sensors, for example in IoT applications. Imagine applications in which thousands of sensors are deployed to monitor the soil moisture in a massive farm for scheduling the watering, or in a forest for the early detection of massive fires. These massive implementations require sensors to work for a long time without a need of human intervention for maintenance. Thus, many researchers focus on overcoming research challenges in this area. Several methods of EH are developed that are powered by sunlight [6], vibration [7], heat [8], and electromagnetic waves [9–11], even from human body movement and heat [12]. However, the amount of the energy that can be harvested from these resources can be uncertain and unpredictable, which can cause difficulties in the design of different network stack protocols [13].

Similar to the effort to prolong the network lifetime in battery powered sensor networks, there are huge efforts on efficiently using the harvested power in energy harvesting sensor networks (EH-WSN), to have longer network lifetime and more reliable performance [14]. One of the ways that researchers have tried to achieve better energy efficiency in EH-WSN is to bring the clustering concept from WSN and try to remodel and adjust the idea to unique characteristics of EH-WSN. Basically, the clustering approach is a way to convert distributed decentralized networks into several small virtually centralized networks, and hence, bringing the benefits of a centralized architecture to a decentralized network [15]. In clustering, the network is divided into clusters, which consist of a cluster-head (CH), gateway nodes (GW) and member nodes (MN). CH is responsible for managing the MNs and processing the members' data, and communication between two adjacent clusters happens through GWs. In a cluster-based WSN, CHs, and GWs form the network backbone [16].

Clustering for EH-WSN can bring the similar benefits that it can bring to conventional WSN. However, considering the unique characteristic of EH-WSN such as an unpredictable amount of harvested power, clustering algorithms need to be carefully designed in a way to efficiently use the harvested power and at the same time try to deal with its uncertainty.

In this paper, we take a closer look at the effect of clustering for EH-WSN. The contributions of this paper are twofold: First is to study the effect of clustering on the performance of EH-WSN and second is to propose a way to improve the performance of the clustered network considering energy harvesting sensors. Therefore, we consider a decentralized network and study the effect of adjusting transmission power in the performance of the network in both flat (non-clustered) and clustered network. Given that the randomness in the transmission power can potentially affect the network topology and in some cases balance the power consumption among nodes with different harvesting ratios, the goal of this paper is to see how clustering can affect network performance in the existence of transmission power adjustment. For clustering, we used a simple energy-based clustering where each node connects to the neighbor with higher available energy. Thus, node A connects to node B as cluster head if node B has higher available power than node A. As cluster heads usually handle more traffic, by using this method, we can assure nodes with higher power become cluster head. However, any other clustering algorithm can be adjusted with the proposed transmission power control method. We show that, even by using a simple clustering concept, the network shows a fairer distribution of power consumption, which results in achieving better network end-to-end performance.

The rest of this paper is organized as follows: Section 2 presents the related work in clustering and power control for energy harvesting sensor networks. The system model is introduced in Section 3. The numerical results are presented and discussed in detail in Section 4. Section 5 presents the conclusion and future work.

2. Related Work

The main design challenge in battery-powered WSN is to prolong the network lifetime by using energy-efficient algorithms and protocols in medium access control (MAC) and Network layers [17,18]. Therefore, energy efficiency has been a very popular keyword in WSN literature. Researchers have been trying to tackle this issue by different means such as proposing methods that directly focus on energy conservation such as sleep scheduling [19], or by proposing energy efficient algorithms such as energy efficient routing, energy efficient medium access control protocol, using clustering [20], and even energy efficient coverage enhancement specially in mobile sensors case [21,22], which perform their classical task more energy efficiently. For example, as is discussed in Reference [19], by carefully selecting a certain number of nodes to be activated to cover a desired portion of a monitored area, network life-time can improve more than 80% in certain areas.

Clustering algorithms, as one of the important ways to reduce the network load and conserve energy, are widely studied in the literature [16]. Like conventional WSN, clustering approaches are widely applied in EH-WSN. However, in EH-WSN, as the amount of harvested energy is uncertain, the protocols should deal with unique challenges and specific characteristics. Several clustering algorithms are proposed for EH-WSN based on the famous Low Energy Adaptive Clustering Hierarchy (LEACH) protocol [23]. One of these extensions is Energy Potential LEACH (EP-LEACH), [24], which predicts the amount of energy that each node might harvest and tries to avoid using a low energy potential node as a cluster head. Using this method, EP-LEACH tries to construct more stable clusters and balance the power. Solar LEACH (sLEACH) is another extension of LEACH for energy harvesting sensors [25]. In sLEACH, the network consists of both solar and battery powered sensors. sLEACH gives higher priority to solar powered sensors with a high level of energy to become a cluster head.

Authors in Reference [26] proposed a centralized genetic-based unequal clustering algorithm for energy harvesting network (EHGUC). The main idea is that a base station creates clusters with different cluster sizes, in a way that the clusters that are closer to the base station will have smaller sizes, so as to make them consume less power. It uses several parameters such as the distance between nodes and energy harvesting rate as weighting parameters to select the cluster head. A gradient-based energy-efficient clustering (GEEC) packet forwarding mechanism is introduced in Reference [27]. Based on the relative position of the nodes and hop counts to the sink, a gradient model is constructed [27]. Cluster heads are selected in a distributed manner by considering the energy harvesting rate and the distance between a CH candidate and the center line of its circular ring. Thus, unequal clusters are formed to lower network overhead and balance network power consumption. The authors in Reference [28] proposed the use of energy harvesting sensors for relaying CH traffic. The concept of clustering is used in [29] to facilitate the routing in EH-WSN. Energy Neutral Clustering (ENC) [30], with the goal of providing perpetual network operation, groups the network into several clusters. It uses a mechanism called Cluster Head Group (CHG), which allows each cluster to have multiple cluster heads to distribute the traffic load. Using this method, the frequency of clustering and control message overhead is reduced. Moreover, using convex optimization techniques, the optimum number of clusters are computed. Another centralized clustering algorithm proposed is Reference [31] uses discrete particle swarm optimization (DPSO) for clustering where base station uses the status of all the nodes to modify the DPSO algorithm for clustering.

Apart from clustering and due to potentially unlimited harvested energy, several authors proposed various ideas about how to efficiently use the harvested power to achieve best performance [32]. One of the ways that is explored is by adjusting transmission power of the nodes. Optimal energy management policies for energy harvesting sensors are considered in Reference [33]. The discounted throughput is maximized over an infinite horizon, where queuing for data is also considered. In Reference [34], the authors proposed a solution to maintain the battery at a certain level in a network with time-varying battery recharging rate. In this work, two algorithms, namely, QuickFix and SnapIt, to compute the sampling rate and routes and to adapt to the rate, are respectively proposed. In Reference [35], to maximize the successful transmission and control energy–error probability tradeoff, Markov

Decision Processes (MDP) have been used to choose between multiple transmissions. The authors in Reference [36] developed a discrete time Markov model for different energy profile and storage capabilities to analyze node outage probabilities. A complete information Markov decision process model is developed in Reference [37] to characterize sensor's battery recharge/discharge process to achieve optimal transmit policies. In Reference [38], the authors used an infinite time–horizon Markov decision process (MDP) to formulate the power control. They obtained a closed-form threshold-based optimal power control solution for EH-WSN. The authors in Reference [39] formulate the power control as a stochastic optimization problem and solve the optimization problem using Lyapunov techniques. Without requiring historical knowledge of energy harvesting only based on the channel fade conditions and current energy state of the battery, their proposed algorithm adjusts the transmission power.

To the best of our knowledge, there is a limited number of contributions in the literature about clustering and power control on energy harvesting sensor networks. However, there are some similar works on conventional battery powered sensors. Li et al. [40] proposes an Energy-Efficient Unequal Clustering (EEUC) mechanism, which partitions nodes into unequal cluster sizes in a way that clusters closer to the base station have smaller sizes than those clusters that are farther away from the base station. Using this method, there would be less power consumption due to intra-cluster data forwarding for cluster heads closer to the base station.

Rehman Khan et al. [41] proposed two routing protocols, namely power-controlled routing (PCR) and enhanced power-controlled routing (EPCR), where the basic idea of both is nodes only change their transmission power when they want to transfer their data to the cluster-heads. Thus, nodes that are closer to the cluster-head can transmit with lower power, which eventually results in less power consumption. The authors in Reference [42] propose a clustering algorithm and a transmission power control mechanism for an ad hoc network, aiming to reduce the impacts of mobility and adaptive transmission power. The idea is that the cluster-head adjusts its transmission power to the changes in its cluster. For example, if CH receives a weak signal from a sensor or a report about unusual error rate, it increases its transmission power to the maximum to cover all the nodes in its vicinity. In another work, the authors in Reference [43] propose a power aware multihop routing protocol for a cluster based sensor network, where the objective is to minimize the power consumption of CH, then it sends the data in a power-aware multihop manner to the base station through a quasi-fixed route (QFR), where nodes vary their transmission power based on the distance to the receiver.

This paper does not aim to propose a novel clustering scheme for energy harvesting sensors, nor does it intend to propose a novel power control scheme for WSN. As energy harvesting is spatio-temporal dependent, nodes might harvest energy with different ratios. Considering this uncertainty in available energy, the main goal of this paper is to study how transmission power control can be effective in a clustered or structured network in EH-WSN.

In our earlier work, we proposed a transmission power control for an unstructured/flat network, where each node sends their data to the base-station that is located in the center of the network using multihop forwarding. We have concluded that the power control can help the load balancing among the sensors in directional communication from sensors to base-station, which results in the better end-to-end performance. However, in this paper, we take a step further to study how power control can affect the performance of the network where there is more dynamicity in the transmission among the nodes. Therefore, we considered a network without any central entity, where sensors communicate together in multihop fashion bi-directionally. Thus, at one round, a node can be a forwarder and at another, it can be the receiver of the packet. We study this dynamicity and randomness in an unstructured network, and then we compare it with a structured network.

The main contributions of this paper can be summarized as follows:

- Studying the effect of power control in an uninstructed network where nodes communicating together in a random multi-hop fashion.
- Studying the adaptive transmission power control effect in the clustered network.
- Comparing the proposed method with some existing work in terms of network lifetime.

3. System Model

We assume there are N sensors deployed non-uniformly in the network, where each sensor is equipped with an energy harvesting unit that is capable of harvesting energy from its ambient environment, e.g., solar, radio wave. The harvested energy is stored in a storage device such as a supercapacitor to supply power for data transmission.

The system operates in a discrete slotted time $t \in \{0, 1, 2, \dots\}$ and all operations are performed in each slot with duration Δt. Let $E_h(t)$ denote the amount of harvested energy, and $E_c(t)$ denote the amount of consumed energy both during time slot t. Let $\rho_c \in (0,\ 1]$ and $\rho_d \in [1, \infty)$ denote charging and discharging efficiency, respectively. Thus, the remaining energy at the beginning of slot $t + 1$ is denoted by $E_r(t+1)$ and is defined as

$$E_r(t+1)\ = \rho_d E_r(t)\ +\ (\rho_c E_h(t)\ -\ E_c(t)) \forall t \tag{1}$$

In this work, for simplicity, the charging and discharging rate of the supercapacitor are considered negligible, thus $\rho_c \approx\ \rho_d \approx\ 1$. Considering E_{max} as the maximum storage capacity, thus $0 \le E_r(t) \le E_{max}$.

In a real-world application, the available harvested energy would be spatio-temporal dependent, which means it varies based on the location of the sensors and time. To emulate this effect, we divide the network in different regions R_i where nodes located in each region harvest with the same probability η_i that is a uniformly distributed random number. Let $E_{h,max}$ and $E_{h,min}$ denote the maximum and minimum harvesting rate, which should satisfy $E_{h,min}\ \le\ \eta_i\ \le\ E_{h,max}$. In this paper $[E_{h,min}, E_{h,max}]$ = [0.5,1] is considered. In a solar powered sensor, 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 $E_{h,max}$, and η_i= 1 represents a clear sky where nodes can harvest energy with the highest ratio.

Based on the remaining energy of each node $i \in N$, $E_{r,i}$, a node i can be in three different states, namely stable, medium, and critical, denoted as $N_{s_i,s}$, $N_{s_i,m}$ and $N_{s_i,c}$, respectively. Thus, for node i, it becomes

$$N_{s_i} = \begin{cases} N_{s_i,s} \quad \text{defines as} \quad E_{r_i} \ge \alpha \\ N_{s_i,m} \quad \text{defines as} \quad \beta \le E_{r_i} < \alpha \\ N_{s_i,c} \quad \text{defines as} \quad \theta \le E_{r_i} < \beta \end{cases}, \tag{2}$$

where α, β, and θ are power parameters that are tunable based on network requirements.

When using transmission power control, for each node, three different transmission power levels are considered, namely, normal, medium, and high, denoted by $N_{tp,n}$, $N_{tp,m}$,and $N_{tp,h}$, respectively. A node switches between these three modes based on its own power level and their neighboring nodes' power condition, as depicted in Equation (3). Therefore, each node adapts its transmission power based on the other nodes' condition in its surrounding environment. Thus, for node i , we have

$$N_{tp_i} = \begin{cases} N_{tp_i,n} \quad \text{if} \quad N_{s_i,c} \ \vee \ N_{s_j,s}, \forall j \in N_{ngh,i} \\ N_{tp_i,m} \quad \text{if} \quad (N_{s_i,s} \vee \ N_{s_i,m}) \wedge \ N_{s_j,c}, \forall j \in N_{ngh,i} \\ N_{tp_i,h} \quad \text{if} \quad N_{s_i,s} \ \wedge \ N_{s_j,c}, \forall j \in N_{ngh,i} \end{cases}, \tag{3}$$

where $N_{ngh,i}$ is the set of node i neighbors in which $N_{ngh,i} \in N$.

In each round (t), a certain number of the nodes N_d generates and transmits their event to a random destination (another node inside the network) over a time-varying wireless channel. The packets are forwarded using neighboring nodes towards the destination in a greedy manner using the shortest hop distance. Therefore, each node might work either as a relay or as a data source or data destination. Therefore, at each round t, node energy consumption is calculated as the maximum power required to sense its own packet or summation of all relayed packets at each round, which can be expressed as

$$E_{c,i}(t) = \max\left\{E_{t_i}(t), \sum\nolimits_{k \in N_{ngh,i}} P_{f,k}(t)\right\}, \tag{4}$$

where E_{t_i} is the energy node i consumes for transmitting its sensing packet and $P_{f,k}$ is the of number of forwarded packets from node i neighbors.

Each node can communicate with the neighboring nodes in its coverage region. A circular region centered on a node is referred to as coverage region of a node, where the radius of the circle can vary, and it is determined by each node transmission power and pathloss model. There are several pathloss models that are used in the literature. In this paper we model the pathloss using log-distance model [44] as follows

$$\overline{P_{R_{dB}}(d)} = P_{T_{dB}} - 10n\log_{10}(d). \tag{5}$$

where $\overline{P_{R_{dB}}(d)}$ is the average received power in dB at separation distance d, $P_{T_{dB}}$ is the transmission power in dB, and n is the path loss exponent. Considering the normal distribution, Equation (5) can be written as

$$P_{R_{dB}}(d) = P_{T_{dB}} - 10n\log_{10}(d) + X_\sigma, \tag{6}$$

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 can be formulated as

$$P_{R_{dB}}(d) \sim \mathcal{N}\Big(P_{T_{dB}} - 10n\log_{10}(d), \sigma\Big). \tag{7}$$

When the receiver sensitivity is lower than the received power, the received signal can be readable at the receiver. Therefore, as $P_{R_{dB}}(d)$ is Gaussian distributed, we use the Q-function to calculate the probability of $P\Big(P_{R_{dB}}(d) > \gamma_{dB}\Big)$ (successful received signal) by calculating the tail probability of the standard normal distribution [44]. Thus, we have

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

Thus, each packet will be successfully delivered to the next hop with a probability of $P\Big(P_{R_{dB}}(d) > \gamma_{dB}\Big)$ at each round. Packets might not reach the destination due to disconnected links, shortage of remaining energy in nodes, or channel conditions. In those cases, the packet will be dropped and measurement outage occurs.

4. Performance Evaluation

As it is costly to have testbed or implementation in a large scale, we have decided to study the performance of the network using MATLAB, where various conditions and different sets of simulations have been conducted using real life parameter values and features that would help us understand the behavior in the design and planning phase of the network. 100 CR sensor nodes deployed non-uniformly in a 1000 m × 1000 m area, which can emulate a 100 hectares' forest. We assume each node is equipped with a supercapacitor such as 3FNESSCAP [45], as 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. Simulation runs for 1000 rounds and in each round 30 randomly chosen sources transfer a packet to 30 randomly chosen destinations using the shortest available path, where several performance metrics such as average packet delivery ratio (PDR), average hop-count, and consumed power are studied. To achieve reliable results, reducing the effect of randomness and obtaining sufficient confidence, we run the simulation with 50 different network setups. Results are averaged with a 90% confidence interval. Simulation parameters are summarized in Table 1.

Table 1. Simulation parameters.

Parameter	Value
Number of nodes	100, 200
Network size	1000 m × 1000 m
Transmission range	Default = 100, Δ = 150, δ = 200 m
Power parameters	A = 50%, β = 25%, θ = 10%
Capacitor	300 energy units
Packet rate	30 packets per round
Energy harvesting rate	6 units per round
Consumption rate	1,3,10 units per round depending on transmission power
Noise Floor	0, 10, 20, 30, 40 dB
Simulation run	50 rounds
Confidence interval	90%

4.1. Non-Clustered Network Performance Evaluation

In the first simulation, a flat (non-clustered) network is considered where each node can communicate with the neighboring nodes within its transmission range. The result of this simulation is depicted in Figures 1–4. Figure 1 depicts an example of a deployed network, with the heatmap highlighting the amount of available energy in the deployment field, where x and y axis defining the size of the field. The figure shows the case with power control ON and OFF. Each case is shown with four subgraphs that are obtained as time evolves in the simulation. As can be observed, the nodes in the center of the network that usually relay more traffic deplete their energy faster than those nodes in the outskirts of the network. However, using adaptive power control, it can be observed that energy is distributed more uniformly than the case without power control.

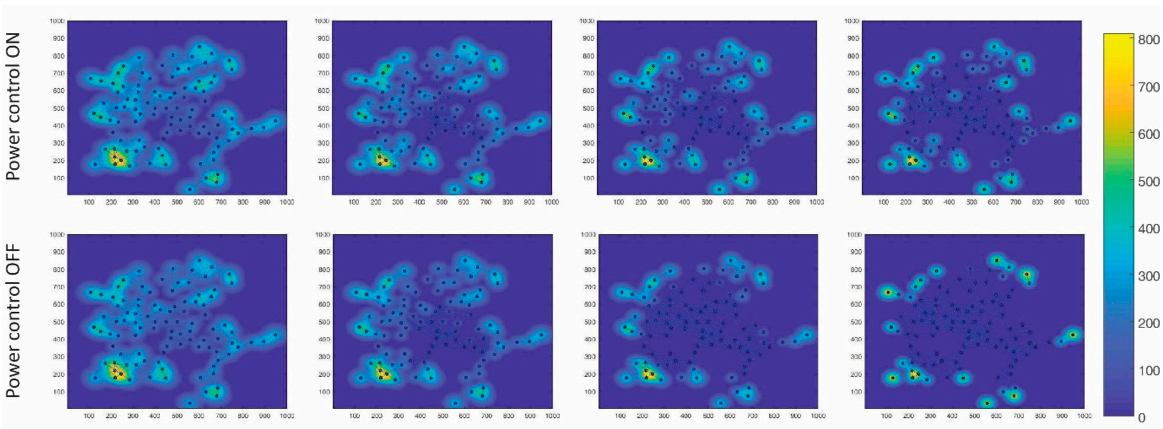
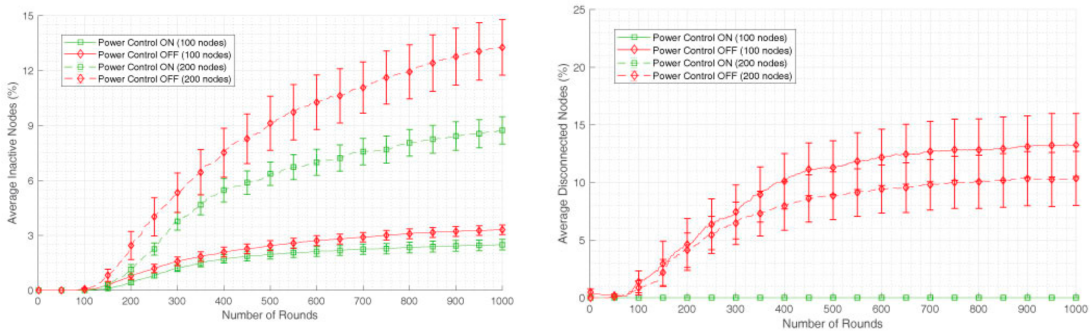


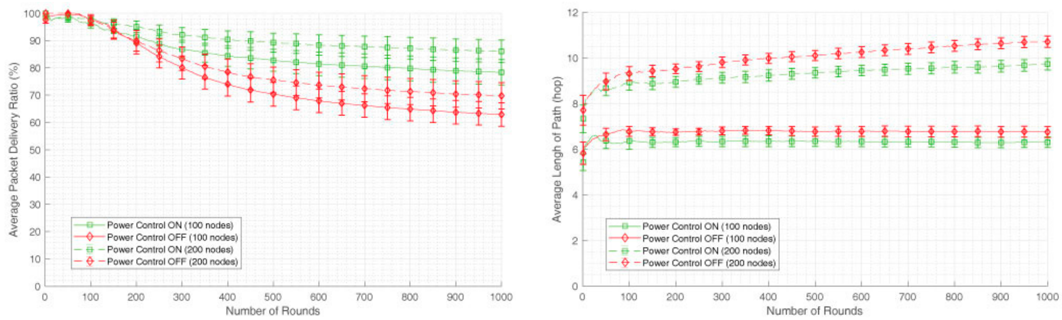
Figure 1. Network power level heatmap demonstrating the changes in the nodes power level in four stages of the running network.

Figure 2 depicts the effect of power control on the percentage of inactive and disconnected nodes. Inactive nodes are defined as those nodes that ran out of power and are deactivated until they harvest enough energy to go back to sensing state. Meanwhile, disconnected nodes are defined as those nodes that have enough power to operate, however, they got disconnected from the rest of the network because of the broken links due to the inactive nodes. As can be observed from Figure 2a, when power control is ON, the network shows a slightly lower number of inactive nodes. The reason is that, by using power control, the nodes balance the energy consumption in a way that they try to reduce the traffic load on low power nodes indirectly forcing them to consume less energy. By increasing the number of nodes to 200, we can see more nodes that are running out of energy, where in round 1000, it reaches 9% and 13%, with and without power control, respectively. The reason behind this sharp increase in the number of inactive nodes can be due to longer hop routes from each source to destination, which causes more energy consumption. The effect of those inactive nodes on the network can be seen in Figure 2b, where the inactive nodes cause a part of the network to be disconnected from the rest. As it is shown earlier in Figure 1, nodes that are usually handling more traffic deplete their energy faster and run out of batteries. As those nodes are usually located in the central area and work as bridges between two sections of the network, their deaths cause network partitioning and disconnected nodes. However, as is shown, using adaptive power control, the network stays connected even in the presence of the same number of inactive nodes as nodes find new connections in the network since nodes can increase their transmission power. By increasing the number of nodes to 200, the network shows lower disconnected nodes due to more connections available that each node has. However, the pattern is still the same.



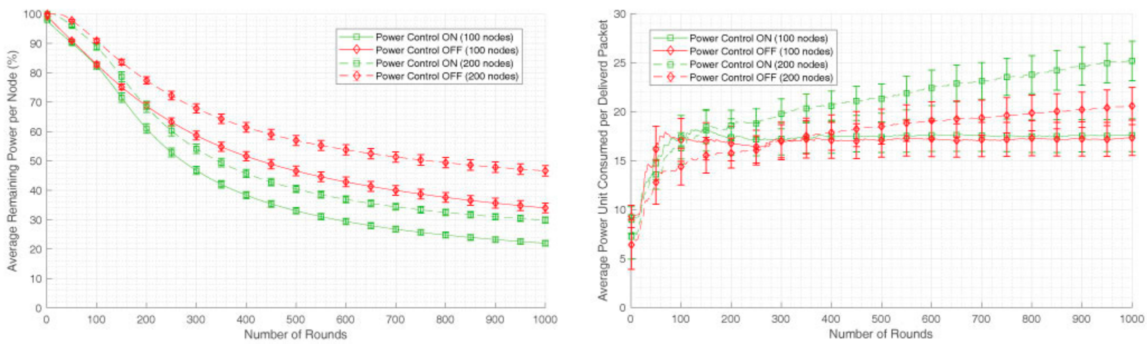
(**a**) (**b**)

Figure 2. Network performance in terms of (**a**) number of inactive nodes and (**b**) number of disconnected nodes.



(**a**) (**b**)

Figure 3. Network performance in terms of (**a**) average packet delivery ratio and (**b**) average length of path.



(**a**) (**b**)

Figure 4. Network performance in terms of (**a**) average remaining power per node and (**b**) average power consumed per delivered packet.

The effect of power control on network end-to-end performance is depicted in Figure 3. The figure reveals that using power control, the network achieves around 20% higher PDR ratio compared to without the use of it, in both 100 and 200 nodes scenarios. The main reason is the number of disconnected nodes from the network in which they cannot reach the rest of the network as observed in Figure 2b. In terms of average hop count depicted in Figure 3b, due to higher transmission range when power control is ON, it shows slightly lower average hop count, which can result in a lower delay. By increasing the number of nodes to 200, the network expands and shows, on average, 2 hop longer routes, but the same behavior.

The network performance in terms of power consumption is shown in Figure 4. It can be observed from Figure 4a that using adaptive power control, the network consumes more energy (as it is expected) and the average remaining energy per node is less than that when not using power control. This is due to the increase in transmission power of some nodes to keep the network connected. It can be seen from Figure 4b that using adjustable transmission power, the network performs the same with and without power control when having 100 nodes, but when having 200 nodes, the network consumes more energy for each packet while using the power control. The reason is again the extra power used in the power control case to keep the network connected. However, considering that it achieves 20% extra PDR (see Figure 3a), it is a reasonable tradeoff.

4.2. Clustered Network Performance Evaluation

Figures 5–8 show the performance of the network where nodes are divided into clusters based on the conditions explained in the system model. Similar to Figure 1, Figure 5 shows the changes in power intensity of a clustered network in different stages. As is shown, using adaptive power control, the network balances the energy consumption in different parts of the network. Compared to Figure 1, it can be observed that, with clustering, the network achieves better energy distribution that results in better performance.

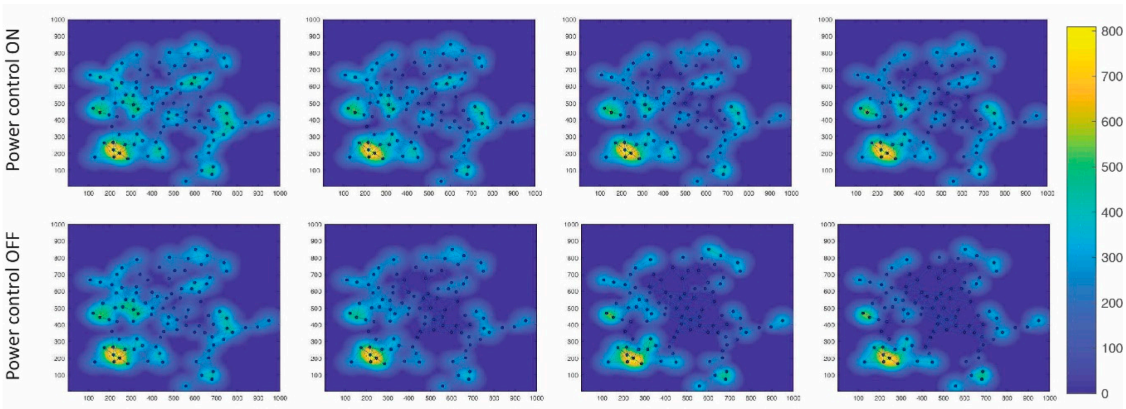
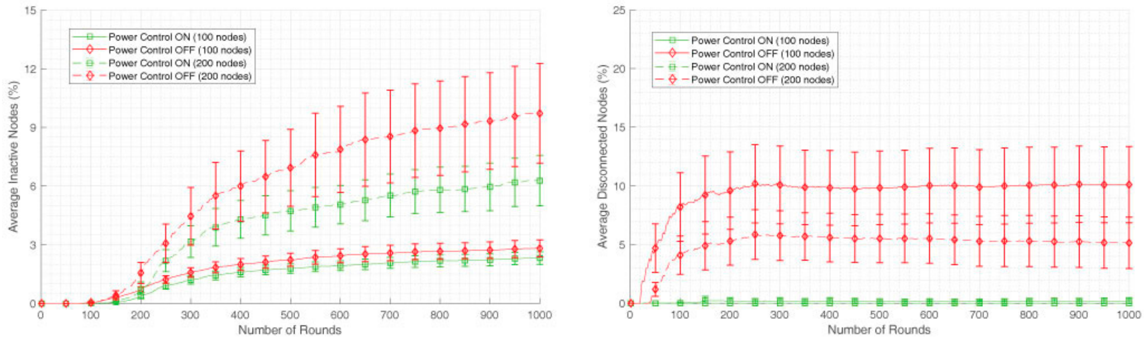


Figure 5. Clustered network power level heatmap demonstrating the changes in the nodes power level in four stages of the running network.

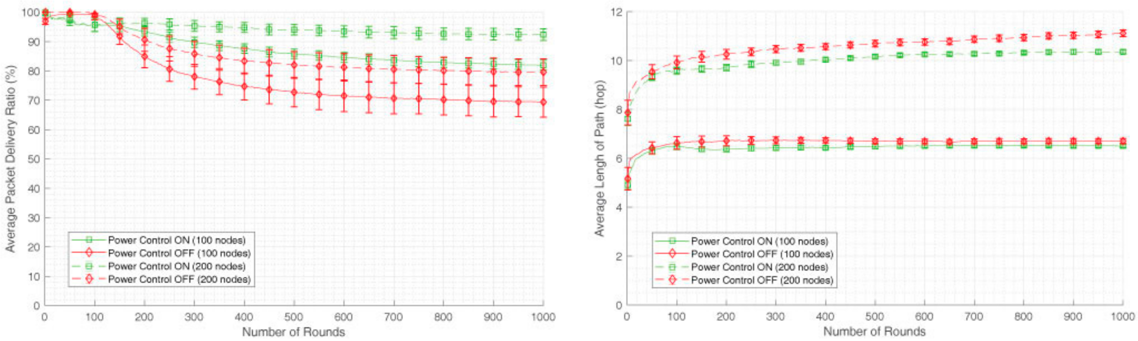
Figure 6 shows the performance of the network in terms of the lifetime of nodes. As can be seen from Figure 6a from round 200, some nodes start running out of batteries. As can be seen, using an adaptable power control network shows slightly lower number of inactive nodes. Like the flat network, in cluster network increasing the number of nodes to 200, we observe more inactive nodes. However, using clustering network shows around 3% less inactive nodes compared to a flat network. Similar to Figure 2b, in Figure 6b, it can also be observed that, due to those inactive nodes, several other nodes get disconnected from the network. However, by adjusting the power control to the network condition, nodes stay connected. Comparing Figures 2 and 6, we can see how clustering in the network improves the performance and we observe a lower number of inactive and disconnected nodes.



(**a**) (**b**)

Figure 6. Network performance in a clustered network in terms of (**a**) number of inactive nodes and (**b**) number of disconnected nodes.

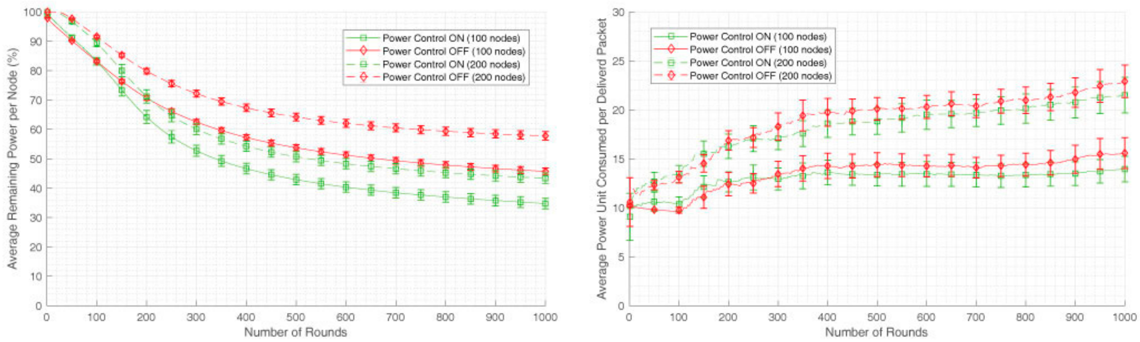
Figure 7 depicts the network end-to-end performance. As can be seen in Figure 7a, without using power control network achieves around 70% with 100 nodes and 80% with 200 nodes, which shows improvement compared to the network without clustering that is around 62% and 70% in the 100 and 200 nodes case, respectively (Figure 3a). The reason behind this improvement is the lower disconnected nodes in the network. While using adaptable power control, the network reaches higher PDR and the performance is similar with the network without clustering and it shows around 80% and more than 90% PDR in the 100 and 200 nodes case, respectively. In terms of average hop-count depicted in Figure 7b, the network shows almost the same pattern with a slight increase in hop count compared to a network without clustering.



(**a**) (**b**)

Figure 7. Network performance in a clustered network in terms of (**a**) average packet delivery ratio and (**b**) average length of path.

Figure 8 shows the network performance in terms of power consumption. It can be seen that, due to an increase in transmission power using adaptive power control network, it consumes more power on average and it drops to nearly 35% and 45% for the 100 and 200 nodes, respectively. However, comparing Figure 8a with Figure 4a, it can be observed that using clustering network results in more than a 10% increase in remaining power per node than when not using it. In terms of packet cost, with and without power control, the network shows the same performance and it consumes 15 power units on average, where this value is 17 units without clustering for 100 nodes. Using 200 nodes, the network shows the same pattern with an increase in packet cost that reaches 20 units per packet.



(a) (b)

Figure 8. Network performance in a clustered network in terms of (**a**) average remaining power per node and (**b**) average power consumed per delivered packet.

A comparison of the proposed protocol with three well-known protocols energy-efficient unequal clustering (EEUC), hybrid, energy-efficient, distributed clustering (HEED) [46], and low energy adaptive clustering hierarchy (LEACH) [47] has been performed in order to study the performance of the proposed protocol. The result of the comparison is depicted in Figure 9. As can be seen from the figure, the proposed protocol start losing some nodes around round 300, while other protocols start performing better. The reason behind is the sudden increase in the transmission power of some nodes in the proposed protocol. However, the rate of dying nodes starts to slow down by round 500. Other protocols maintain most of the nodes' power, but they face a sudden decrease in the number of alive nodes, as by then, most of the nodes lost their high percentage of power. As can be seen, by round 700 to 800, most of the nodes are dead in the other protocol, while the proposed protocol shows better performance having around 50% of the nodes alive. The reason is that nodes are relaying lower traffic due to the loss of some connections.

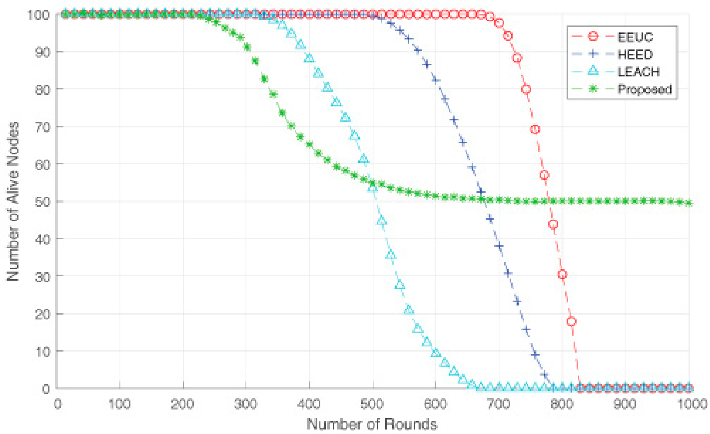


Figure 9. Performance comparison regarding the network lifetime.

5. Conclusions

Energy harvesting is a sustainable way to prolong lifetime of a sensor network, which enable us to target various applications that are not feasible using battery-powered sensors. However, the uncertainty in the amount of available energy poses design challenges. This paper studied the effect of using adaptive transmission power control for energy harvesting sensors in both clustered and non-clustered networks. The adaptive transmission power control adjusts the transmission power of each individual node independently based on the node residual power and its neighboring nodes' energy condition. Once a node energy level goes below a predefined threshold level, the neighboring nodes increase their transmission power control based on their residual power accordingly, to reduce the traffic load on the low energy node. Using this method, power can be consumed more uniformly among the nodes in the network. The numerical results indicate that the proposed adaptive transmission power control improves the performance of non-clustered networks. We also have proven that a basic power control can still improve the clustered network performance further and help the network to achieve better end-to-end performance. In this paper, we have used a simple energy-based clustering, greedy routing, and relatively simple power control mechanism to prove the efficiency. However, in the future other clustering and routing algorithms are going to be considered, which we believe results in further improvement of network performance metrics.

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