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On transmission range of sensors in sparse wireless sensor networks

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ABSTRACT

One of the main challenges in the design of wireless ad-hoc and sensor networks is to reduce energy consumption and radio interference and collision, which are strictly and strongly correlated to the transmission range of the nodes. In this article, the transmission ranges of sensors in sparse Wireless Sensor Networks (WSN) is theoretically analyzed and is shown that the transmission ranges of sensors can be significantly reduced in this type of WSNs without losing any connection. Next, a method is presented to calculate reduced transmission ranges. In this method, an iterative transmission range adjustment mechanism is used to select an almost transmission range while no information is needed on the location of nodes or the distance between nodes. This method is very efficient and its communication overhead is low. It can be used as a pre-step of any routing algorithm in order to decrease energy consumption and radio interference in targeted scenarios. The simulation results show the efficiency of the proposed method. We got at least 50% improvement in energy consumption in comparison with full power network, in sparse WSNs.

1. Introduction

Wireless Sensor Networks (WSNs) have become increasingly popular in recent years, as they offer a powerful and cost-effective solution for monitoring and collecting data from a variety of environments. A Wireless Sensor Network (WSN) consists of a large number of distributed sensor nodes that cooperatively monitor the physical world [1]. Each node in these networks is typically equipped with a wireless communication device, a small microcontroller, a memory unit and a power source. The nodes in a WSN are typically battery-powered and have limited processing power, memory, and communication bandwidth. Therefore, the design of a WSN requires careful consideration of these constraints, such as the choice of communication protocol, data routing algorithms, and energy management strategies [2].

The complexity of the WSN domain as well as the presence of many sensor nodes unavoidably introduces a large amount of data in these networks that must be processed, transmitted and received. The sheer amount of data generated by WSNs can pose a significant challenge for the network design and operation. The sensors in a WSN can generate data continuously or periodically, depending on the application requirements. This data must be processed, stored, and transmitted to the base station in a timely and efficient manner. So the complexity of the WSN domain and the presence of many sensor nodes can introduce a large amount of data that must be processed, transmitted, and received [3]. Despite their profound advantages, the utilization of WSNs is often battery-powered and strictly limited due to energy constraints. In fact, most of the energy expenditure of a sensor node occurs during wireless communication, and the remaining energy is consumed during sensing and data processing. The radio transceiver of a node consumes a significant amount of energy during data transmission and reception. Therefore, the energy consumption of a node must be carefully managed to ensure the longevity of the network [4]. Transmission power adjustment for a special transmitter-receiver pair depends on several environmental conditions. The transmission power required to reach the receiver is affected by two main factors including distance and wireless connection quality. Distance affects transmission power. As the distance between the transmitter and receiver increases, the signal strength decreases, resulting in a weaker connection. To maintain a reliable connection, the transmitter must adjust its power output to compensate for the signal loss due to distance. The quality of a wireless connection can be impacted by various factors, including interference from other wireless devices, climatic conditions, physical barriers, obstacles between the transmitter and receiver, and signal-to-noise ratio. In a noisy environment, the transmitter may need to increase its power output to overcome the interference and maintain a reliable connection. On the other hand, in a low-noise environment, the transmitter may be able to

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reduce its power output to save energy and avoid interfering with other nearby wireless networks. At a given connection quality, the transmission power is adjusted so as to maintain a good connection that promotes the success of the data delivery [5–7]. Instead of transmitting the maximum possible power, nodes in a wireless multi-hop network collaboratively decide their transmission power and establish the topology of a wireless network by a neighbor relationship under certain conditions. This compares with the "traditional" network in which each node transmits its full transmitting capacity, and the topology implicitly constructs routing protocols that update its routing caches as quickly as possible, without considering the power issue. By collaboratively determining transmission power levels, nodes in a multi-hop network can optimize their energy consumption and reduce interference with other nodes. This is particularly important in multi-hop networks where nodes are often battery-powered and have limited energy resources. By minimizing power consumption, the network can extend the lifetime of the nodes and increase the overall network efficiency. The establishment of the network topology based on neighbor relationships allows for the creation of efficient routing paths between nodes. Nodes can communicate with neighboring nodes that are within range, rather than relying on a centralized router to manage the flow of information. This approach reduces the need for infrastructure, improves network resilience, and allows for greater flexibility and scalability [8,9].

In some cases, particularly in the case of sparse wireless sensor networks, there is no need to transmit a message with the maximum transmitting power of the sensor in order to reach all its neighbors [10]. In these cases it is worthwhile to calculate the distance between a sensor and its farthest neighbor, and to decrease the transmission range of sensor to this distance. By reducing the transmission range of sensors to match the distance to their farthest neighbors, energy consumption can be minimized and the lifetime of the nodes can be extended. This is particularly important in scenarios where nodes are battery-powered and have limited energy resources. By minimizing energy consumption, the network can operate for longer periods of time, reducing the need for frequent maintenance and replacement of nodes.

The present research is an extension to our previous work that was presented in Ref. [11]. However we do not consider the theoretical analysis in that paper. In this article, we theoretically analyze the network and our proposed method and its expected improvement, furthermore we analyze the communication and computational complexity of our method, and furthermore the simulation section is extended.

The rest of the paper is organized as follows. In Section 2, the related works in the field of transmission power control and topology control are summarized. A description of system model and a theoretical analysis of the distance between a node and its farthest neighbor is presented in Section 3. In Section 4, the proposed transmission range adjustment method is presented. Energy consumption and complexity analysis come in Section 5. Simulation-based performance evaluation is discussed in Section 6. Finally, a conclusion and our vision to future research topics and challenges are offered in Section 7.

2. Transmission power control

In this section we survey some works in the field of Transmission Power Control (TPC) and Topology Control (TC) in wireless sensor networks. We survey some works which are more similar to our work and are fully distributed.

The common concept of the various schemes proposed is to dynamically change the transmission power in order to detect and maintain a good connection between a pair of nodes instead of transmitting data at full power [12]. A good connection is defined as a connection between a receiver-transmitter pair which supplies successful data delivery [13]. The common TPC procedure in WSNs is monitoring the current connection quality by broadcasting messages to neighbors and then evaluating the incoming acknowledgements. There is a similar concept called "Topology Control" which aims to control the topology of a graph representing communication connections between network nodes with the aim of preserving some global graph property (e.g. connectivity) while at the same time reducing energy consumption and/or interference that is strictly related to the node transmission range [14].

The authors of [15] proposed two distributed algorithms to dynamically adjust the transmission power level on a per-node basis, Local Mean Algorithm (LMA) and Local Mean of neighbors Algorithm (LMN). A core assumption of this work is that each sensor utilizes the same transmission power level for sending packets to all of its neighbors. The algorithms were designed to be integrated with routing protocol which can take some benefits from the per-node power level information. These algorithms are scalable and do not need global information. The LMA works as follows: All nodes start with a similar initial transmission power (TransPwr). Every node periodically broadcasts a life message (LifeMsg) including its unique identity. All other nodes that receive such a LifeMsg respond with a life acknowledge message (LifeAckMsg) response, including the LifeMsg sender address. The number of LifeAckMsgs obtained (NodeResp) is counted before a node issues the next LifeMsg. If NodeResp is less than the minimum threshold (NodeMinThresh), the node increases its transmission power by a certain Ainc factor; the transmission power is not increased by more than a Bmax factor in a single stage. If NodeResp is larger than the maximum threshold (NodeMaxThresh), it reduces its transmission power by a certain *Adec* factor for each supernumerary neighbor; the transmission power is not reduced by less than *Bmin* in a single stage.

The "Local Mean of Neighbors" (LMN) algorithm works like LMA with the exception of that it adds some details to LifeAckMsg and determines NodeResp in a different way. According to the LMN approach, the number of neighbors of the receiver is applied to the life-acknowledgment set. After a transmitter receives acknowledged packets from all of its neighbors, it calculates a mean value of the number of its neighbors' neighbors. This calculated value is used instead of the number of counted acknowledged packets. The power adjusting mechanisms are similar to the LMA. These local algorithms are superior to fixed power level assignment algorithms.

It is not specified how to calculate values of different thresholds used in these two algorithms, while the performance of these algorithms is highly affected by the values of these thresholds. Also the communication overhead and energy consumption overhead of algorithms are not analyzed. Furthermore, the connectivity of network is not guaranteed.

The authors in Ref. [16] presented Transmission Power Control (TPC), a new scheme including two steps of operation. The main goal is to maintain the number of neighbors within the range desired. The notion of an efficient neighbor is used to change the radio transmitting power to the right level. A node *ne* is an efficient neighbor of *na* if *na* knows that *ne* can receive beacon messages from *na*. Using the following protocol a sensor node can say their number of successful neighbors (N):

1) Each node *na* sends a beacon message.
2) A node *ne* that receives a beacon message from *na* with a connection quality that is better than the predefined threshold *RSSthreshold* records the source ID of the message. When the node sends a beacon message, the list of neighbors on the beacon message is piggybacked.
3) Node *na* hears a beacon message from *ne* and it can tell whether *ne* has heard *na* by looking at the neighbor list piggybacked on the beacon message. Node *na* counts all such *ne's* that have heard *na*.

After finding the number of neighbors, the algorithm adjusts the radio transmission power so that the number of effective neighbors *N* converges to a predefined value *Ntarget*.

The transmission power will be increased if the number of neighbors observed is less than the predefined value. The algorithm is capable of reducing the degree of adjustment as the number of neighbors converges to the targeted value. This scheme provides flexible degree of adjustment based on the number of neighbors. However, it is particularly designed for convergence and aggregation traffic patterns.

Similar to previous work it is not specified how to calculate the values of different thresholds used in this algorithm, the communication overhead and energy consumption overhead of the algorithm is not analyzed, furthermore the connectivity of network is not guaranteed.

The authors of [17] proposed a lightweight Adaptive Transmission Power Control (ATPC) algorithm for wireless sensor networks. In ATPC, each node builds a model for each of its neighbors, explaining the correlation between transmission power and link quality. In this model, a feedback-based transmission power control algorithm is employed to dynamically preserve individual connection quality over time. The contribution of this work lies in a pairwise transmission power control. Each node allocates a various minimum transmission power for each connection. Two main ideas behind its design are a neighbors table maintained by each node and a closed loop for transmission power control running between each pair of sensors. The table entries include node ID, the appropriate transmission power levels defined as the minimum power which provides a good connection quality and several parameters used for linear predictive models of transmission power control. The closed loop feedback is used to obtain the minimum transmission power by gradually adjusting the power. ATPC has two phases including initialization and run-time tuning phases. In the first phase, a predictive model is called and used to calculate the proper power level for each neighbor. A sensor broadcasts beacons to all of its neighbors at different power levels. Upon receipt of the beacons, the neighbors calculate both LQI (Link Quality Indicator) and RSSI (Radio Signal Strength Indication) values. They send these values back to the transmitting node as a feedback. Note that the predictive model is initially used only to estimate the right power level. Power level variation is then performed for each pair of nodes to track the actual connection conditions. After the initialization process, a sensor looks up the generated table when the data has to be sent. The actual quality of the connection can be obtained after the receiver sends both LQI and RSSI values back to the transmitter. A connection quality monitor module determines whether a notification message is needed. The main duty of this module is to monitor the connection quality and to generate a notification only when the link quality is below the desired level or the current signal is too high. On receipt of notification, the transmitter changes the correct transmission power.

In this research the computational overhead and the energy consumption overhead of the algorithm are not analyzed. Furthermore in the initialization phase of algorithm, each node needs global information about all of its neighbors.

In [18–20], Transmission Power Control and Blacklisting (PCBL) and Real-Time Power-Aware Routing Protocol (RPAR) are introduced, which are two transmission power control algorithms for specific scenarios. The main ideas of both algorithms are similar to the surveyed works.

In the field of topology control, there are some works that they require location information. The authors of [21,22] presented a distributed topology control algorithm and proved that the proposed topology minimizes the energy required to communicate with a given master node. The authors of [23,24] proposed a more efficient implementation of the protocol. However, the new implementation computes only an approximation of the minimum energy topology. The authors of [25,26] introduced LMST, a fully distributed and localized protocol building an MST (Minimum Spanning Tree) like topology.

A weakness of all of these three algorithms is that they require location information which can be provided only with a considerable hardware and/or message cost.

Another class of topology control protocols is based on the simple idea of connecting each node to its k nearest-neighbors.

The authors of [27,28] have defined the MobileGrid protocol which attempts to keep the number of a node's neighbors within a low and high threshold around an optimum value. When the number of neighbors is below (above) the threshold, the transmission range will be increased (decreased) until the number of neighbors is within the appropriate range. In Ref. [29], the authors introduced LINT protocol which is similar to MobileGrid protocol.

However, the characterization of the optimum value of the number of neighbors is not provided for both protocols and the connectivity of the resulting communication graph is not guaranteed. Another problem with the MobileGrid and LINT protocols is that they estimate the number of neighbors by simply overhearing control and data messages at different layers. This method has the advantage of not producing a control message overhead, but the accuracy of the resulting estimation of the neighbor number depends heavily on the traffic present in the network. For example, none of its neighbors can detect a node which remains silent.

There are also some distributed topology control protocols based on directional information such as those introduced in Refs. [30–32].

Wireless communication, however, is also distinguished by the phenomenon of multipath propagation in which the signal reaches the receiving antenna via two or more paths [33–35]. In addition, there are many other types of radio irregularities that have an effect on the topology control algorithms [36]. The various paths, with variations in delay, attenuation, and phase shift, make it difficult for the receiving node to deduce its distance from the sender and the sender's direction.

In some works some theoretical analysis are presented. In Ref. [37], the authors presented a graph – theoretic formulation of the channel assignment, led by a novel perspective for the control of topology, showing that the resulting optimization problem is NP-complete.

The authors of [38,39] proposed a novel control of topology focused on opportunities. The authors have shown that opportunity-based topology control is a NP-hard problem. To address this problem in a practical way, they designed a completely distributed algorithm called CONREAP based on reliability theory. They have proven that CONREAP has a guaranteed performance.

There are also many researches in the field of topology control in the recent years. The main idea is similar to previous woks, tracking the consistency of the current connection by transmitting messages to neighbors and then evaluating the incoming acknowledgements. But each work has some contributions and specifications, like works presented in Refs. [40,41].

We propose a method to overcome some of the weaknesses of the surveyed methods like requirement of location information, requirement of direction information, and requirement of thresholds values, high communication overhead or high processing overhead. Furthermore, we present a full theoretic analysis of our algorithm and compute the expected energy consumption improvement caused by using our proposed algorithm. Based on the best of our knowledge, none of the surveyed algorithms has a theoretic analysis or theoretic computation of expected improvement by using the algorithm. Furthermore we check our theoretical results by simulation. The presented theoretical analysis results could be used for analyzing the other TPC methods in wireless sensor networks.

3. Farthest neighbor

In this section, first we describe the model we used to analyze the problem. Next, we analyze the distance between an arbitrary sensor u and its farthest neighbor.

The same model is utilized just as in Ref. [42]. In this work, the wireless sensor network is considered to be a network of homogeneous sensors referred to as *nodes*. All nodes are arbitrarily (using random uniform probability distribution) deployed in a two-dimensional plane. Each node is equipped with an omni-directional antenna with adjustable transmission power. Since nodes are homogeneous, they have same maximum transmission powers and radio ranges. For node i, we use P_i to denote its transmission power, P_i^{max} as its maximum transmission power (or, alternatively, *full power*). Assuming that the transmission medium is symmetrical (and that asymmetrical connections are just attributable to the different ranges), any two nodes u and v can directly communicate with each other if their Euclidian distance is less than a communication range R_c, *i.e.*, $|uv| < R_c$. Due to the non-existent asymmetric links, the topology where each node transmits with its maximum transmission power is naturally an undirected graph, referred to as the *maximum topology* $G = (V,E)$. G can be either connected, or disconnected. In a *connected* G, there is a possibly multi-hop path from any source to any destination. In a *disconnected* G, there are pairs of nodes that cannot reach each other. We use the path loss model commonly adopted by previous works [43–45]. The power of the received signal has a distance dependence of $\frac{1}{d^n}$, where d is the propagation distance and exponent n ranges from 2 to 6 depending on the environment. So the energy consumption for transmitting a message is proportional with d^n and is not linear to the distance. We further assume that other information such location information (x_i, y_i), or distance between nodes is not available for all nodes in the network.

Now we consider a sensor network that its nodes are randomly deployed in a two-dimensional plane using a uniform probability distribution. We choose an arbitrary sensor u and analyze the distance between this node and its farthest neighbor. We assume a communication range R_c for all nodes. So, all of neighbors of each node are in a region with area πR_c^2.We consider a typical node u, and one of its neighbors v. The probability that the distance between u and v to be exactly r is $\frac{2\pi r}{\pi R_c^2}$. If the density of network is such that every node has *1* neighbor on average, this single neighbor is the farthest neighbor, and r is the distance between u and its farthest neighbor. The r can be every value between 0 and R_c, so we can calculate the expected value of r as follows:

$$\bar{r} = \int_0^{R_c} \frac{2\pi r}{\pi R_c^2} * r dr = \frac{2}{3} R_c \quad (1)$$

Now we consider a scenario that the density of network is such that every node has k neighbors on average, where k is an arbitrary number. If the distance between u and its farthest neighbor is exactly r, then the distance of one of the k neighbors of u must be exactly r, and the distance of other neighbors must be less than or equal to r. The probability that the distance between u and one of its neighbors to be less than or equal to r is $\frac{\pi r^2}{\pi R_c^2}$ (Assuming a random deployment with uniform probability distribution, the probability of that a node in region A is located in a sub region of A like A' is $\frac{Area(A')}{Area(A)}$), also we know the probability that the distance between u and one of its neighbors to be exactly r is $\frac{2\pi r}{\pi R_c^2}$.

Deployment of each node is independent from deployment of other nodes so the probability that the distance between u and its farthest neighbor is exactly r can be calculated as follows:

$$k * \frac{2\pi r}{\pi R_c^2} * \left(\frac{\pi r^2}{\pi R_c^2}\right)^{k-1} \quad (2)$$

We can choose the farthest neighbor in k ways. The probability that the distance of this neighbor is exactly r is $\frac{2\pi r}{\pi R_c^2}$. The distance of other k - *1* neighbors must be less than or equal to r. The probability of this is equal to $\left(\frac{\pi r^2}{\pi R_c^2}\right)^{k-1}$. r can be every value between 0 and R_c, so we can calculate the expected value of r as follows:

$$\bar{r} = \int_0^{R_c} k * \frac{2\pi r}{\pi R_c^2} * \left(\frac{\pi r^2}{\pi R_c^2}\right)^{k-1} * r dr = \frac{2k}{2k+1} R_c \quad (3)$$

As we can see in the above formula if the sensor network is sparse and each node has few neighbors, difference between R_c and $\bar{r}$ is significant, and it is worthwhile to decrease the transmission range of u from R_c to $\bar{r}$.

4. The proposed algorithm

The current methods for deploying sensor nodes in environment are not accurate and the position of nodes in different deployment could be different. For example, a typical way of deployment in a forest would be tossing the sensor nodes from a plane. So it would be useful if the sensors can adopt themselves with environment and can adopt their transmitting range according to their position in each deployment and can learn the best transmitting range which is less than the maximum possible transmitting range of sensor, but the sensor can send its messages to any sensor in its transmitting range. In other words, our goal is to set the transmitting range of each sensor to maximum distance from the sensor, where another sensor is existing, and this distance is less than the maximum possible transmitting range of the sensor. According to the nature of sensor networks, there may be many sensor failures due to different reasons. The farthest node (a) to another node (b) may become out of order, so there is no need to set the transmitting range of b such that b can transmit messages to a. Thus, we can update the transmitting range of sensors periodically to adopt the network with these failures.

If every sensor knows its precise location and its neighbors' locations, there is no need to run any algorithm. In this case, each node can itself compute the required transmitting range easily. But in real scenarios the sensors initially does not have any information about their neighbors' locations. If such information is available, there is a high communication overhead (and high energy consumption) to exchange this information between sensor nodes. Furthermore, since the devices needed to have precise location information of nodes are expensive and consume high amount of energy, in many applications we do not have such information.

We propose a method to overcome some of the weaknesses of the surveyed methods like requirement of location information, requirement of direction information, and requirement of thresholds values, high communication overhead or high processing overhead. Furthermore, we present a full theoretic analysis of our algorithm and compute the expected energy consumption improvement caused by using our proposed algorithm.

Now we describe our algorithm which is based on a distributed learning approach and is similar to binary search and have a low communication overhead at each time it executed, we name our method as Simple Transmission Power Control (STPC).

When the algorithm is executed, in first step every node i transmits a message, referred to as **R**equest **T**o **R**esponse (***RTR***) message, using its maximum transmission power P_i^{max}. Set of nodes that receive the ***RTR*** message are referred to as the vicinity nodes of node i, denoted as V_i. Upon receiving such a ***RTR*** message, each node j in V_i replies to node i with an acknowledge (***ACK***) message using its maximum transmission power P_j^{max}. Now every node i saves the number of nodes transmitting ***ACK*** message to its ***RTR*** message ($\mathbf{n}\{V_i\}$). In second step of algorithm every node i transmits a (***RTR***) message using half of its maximum transmission power $\frac{1}{2}P_i^{max}$, and calculate the number of nodes that transmit ***ACK*** message to its ***RTR*** message. If this number is less than $\mathbf{n}\{V_i\}$, there are some nodes that receive the previous ***RTR*** message of the node i, but do not receive the second ***RTR*** message. So we use the $\frac{3}{4}P_i^{max}$ for transmitting the ***RTR*** message in the next step of algorithm. But if the number of nodes transmitting ***ACK*** message to its ***RTR*** message is equal to $\mathbf{n}\{V_i\}$, we use $\frac{1}{4}P_i^{max}$ for transmitting the ***RTR*** message in the next step of algorithm. We continue this approach like binary search for $\mathbf{n}$ steps. We decrease (increase) the transmitting power of ***RTR*** message in the next step of the algorithm according to the number of nodes sending the ***ACK*** message to the node i. If this number is equal to previous step, we decrease the transmitting power. If this number is less than the number calculated in the previous step, we increase transmitting power of ***RTR*** message in the next step. We change the transmitting power of ***RTR*** message in step l of the algorithm by $\frac{1}{2^l}P_i^{max}$. Using this method with n steps, every node learns the best transmitting power to not lose any possible connectivity with precision of $\frac{1}{2^{n+1}}P_i^{max}$. The optimal value for transmitting power to not lose any possible connectivity is the minimum power required to reach the farthest neighbor of each node; but because we don't use any location information we can't calculate this optimal value, and calculate a near optimal value (with precision of $\frac{1}{2^{n+1}}P_i^{max}$) for transmitting power of each node.

Every message used in this algorithm is **2** byte including **1** bit for message type and **15** bit for node ID. The pseudo code of STPC algorithm (with n steps) is as follows:

For each node **i** do

1. Set the transmitting power of node **i** to P_i^{max}, **TP(i)**$=P_i^{max}$.
2. Send a **RTR** message using **TP(i)** transmitting power
3. Calculate the number of received **ACK** messages and name this value as $\mathbf{n\{}V_i\mathbf{\}}$
4. Set $\mathbf{NRA(i)} = \mathbf{n\{}V_i\mathbf{\}}$
5. diffPow $= \frac{1}{2}P_i^{max}$

For $\mathbf{c} = \mathbf{2}$to **n** do
For each node **i** do

1. If $\mathbf{NRA(i)} = \mathbf{n\{}V_i\mathbf{\}}$ then

TP(i) = TP(i) − diffPow
Else
TP(i) = TP(i) + diffPow

2. Send a **RTR** message using **TP(i)** transmitting power
3. Calculate the number of received **ACK** messages and put this number in **NRA(i)**

diffPow = diffPow/2

This algorithm has many advantages, first of all this algorithm is very simple and does not need any information about location of nodes, distance between nodes, the strength of received signal, direction of nodes, direction of received signals or other such information, and just needs the information about receiving or not receiving a message.

The second advantage of this algorithm is its scalability. This algorithm is a fully distributed algorithm to be executed on each node in the network. Since every node in the network can run the algorithm independently based on its local information, despite the size of the network, the execution of our algorithm is limited to its vicinity topology only. Moreover, the message exchange is restricted to its vicinity topology as well. Thus, our algorithm is scalable to networks composed of a large number of nodes. Furthermore, due to the asynchronous execution at each node, our algorithm reduces the control overhead for synchronization when networks get larger, so it is scalable to larger networks.

But this algorithm cannot be executed in dense sensor networks, because the communication overhead would be high and the expected performance improvement is small. Also in these networks the algorithm is prone to collisions. In sparse sensor networks, we can solve collisions problem by using a timing mechanism and some retries, but these mechanisms cannot be used in dense sensor networks.

According to failure rate of sensors and the expected number of bytes that each sensor transmits, we can choose periods to execute this algorithm periodically and adjust the transmitting range of sensors.

5. Analysis

In this section we theoretically evaluate the efficiency of our proposed algorithm in terms of energy consumption. Furthermore, we give a complexity analysis for our proposed algorithm.

5.1. Energy consumption analysis

As already mentioned, the consumed energy for transmitting **1** byte data to distance d is proportional to d^m, where exponent m ranges from **2** to **6** depending on the environment. So we can suppose the consumed energy for transmitting **1** byte data is $e = c * d^m$ where c is a constant, by this assumption if each sensor has k neighbors(on average), the consumed energy for executing each step of the algorithm is at most:

$$e = c * 2(k+1) * R_c^m \tag{4}$$

Because the length of each message is **2** byte, maximum transmission range is R_c and at most $k+1$ messages transmitted in each step of algorithm (**1 RTR** message and at most k ***ACK*** messages). So the total amount of energy consumed for executing the algorithm with n step is at most:

$$n * c * 2(k+1) * R_c^m \tag{5}$$

If we name the transmission range calculated by proposed algorithm as r_n , after executing this algorithm we transmit each message to distance r_n instead of R_c. Thus the saved energy for transmitting **1** byte is $c * (R_c^m - r_n^m)$.

According to equation calculated in section 3 and the proposed algorithm, the mean saved energy is:

$$c * \left(R_c^m - \left(\left(\frac{2k}{2k+1} + \frac{1}{2^{n+1}}\right)R_c\right)^m\right) \tag{6}$$

The wireless medium is highly volatile, and thus a link can be easily lost if the transmission power and receiving antenna gain are on the borderline. To avoid this risk, we add an extra term of $\frac{1}{2^{n+1}}R_c$ to transmission range calculated by the proposed algorithm.

So the mean saved energy is:

$$c * \left(R_c^m - \left(\left(\frac{2k}{2k+1} + \frac{1}{2^{n}}\right)R_c\right)^m\right) \tag{7}$$

Thus if each sensor transmits at least

$$\left[\frac{\textit{Overhead of Algorithm}}{\textit{mean saved energy for transmitting } \text{each } \textit{byte}}\right] = \left[\frac{n * 2(k+1) * R_c^m}{R_c^m - \left(\left(\frac{2k}{2k+1} + \frac{1}{2^n}\right)R_c\right)^m}\right] = \left[\frac{n * 2(k+1)}{1 - \left(\frac{2k}{2k+1} + \frac{1}{2^n}\right)^m}\right] \tag{8}$$

Bytes of data after running the proposed algorithm, we save more energy than energy we have consumed to execute the algorithm. For example if $n = 10$, $m = 4$ and $k = 5$, if we transmit **383** bytes per each sensor we will save more energy than energy consumed for executing the algorithm. According to expected lifetime of sensor networks (for example at least **6** months) and application of sensor networks, it is expectable that each sensor transmits at least **10000** bytes of data in its lifetime. So executing this algorithm in sparse sensor networks is worthwhile in terms of energy consumption.

The term *Sparse* Sensor Network in this work is used for Sensor Networks that executing the proposed algorithm is worthwhile in them. This issue depends on application of sensor network, maximum transmission range of each node and density of network. For example in applications which sensors deliver high amount of data to the sink, the number of neighbors of each node could be more than this number in applications with low communication traffic, and the sensor network is still referred as a sparse sensor network in this work. For example, in applications where sensors deliver a high amount of data to the sink, the number of neighbors of each node could be greater than in applications with lower communication traffic. However, even in such cases, the sensor network can still be referred to as a sparse sensor network if the density of the network is low enough to justify the use of the proposed algorithm or technique. The benefits of using a sparse sensor network approach can include reduced energy consumption, increased network lifetime, and improved data accuracy and reliability. By targeting specific areas of the network and optimizing the use of resources, a sparse sensor network can often outperform more general approaches that treat all nodes and data equally. Overall, the concept of a sparse sensor network highlights the importance of tailoring the design and implementation of sensor networks to specific applications and environments. By understanding the unique characteristics of each network and applying appropriate techniques and algorithms, it is possible to achieve more efficient and effective data collection and analysis.

5.2. Complexity analysis

In this section, we analyze the communication complexity and the computational complexity of our algorithm. Furthermore, we compare our proposed method's communication and computational complexities with some of the transmission power control algorithms that do not use neighbors to share location-based information.

In our analysis, we assume bidirectional communication. Therefore, the maximum out-degree (Δ^+) and the maximum in-degree (Δ^-) of all of nodes in communication graph are identical. We denote the maximum node-degree of the original communication graph by $\Delta = \Delta^+ = \Delta^-$. Furthermore, we do not use the size of the ID in our study when calculating the complexity of communication. It is because the sensor node IDs are likely to be globally unique to each node and allocated by the supplier, as in the case of Ethernet cards. We therefore expect the ID sizes to be independent of the scale of the network deployment of the sensor.

As we stated in previous section, at each step of our proposed algorithm for each node at most $\Delta + \boldsymbol{1}$ messages are transmitted (**1 RTR** message and at most Δ ***ACK*** messages to ***RTR*** message of this node). Furthermore, we know that at each step of our proposed algorithm each node transmits at most $\Delta + \boldsymbol{1}$ messages. Because we assume bidirectional communication and if node ***a*** is a neighbor of node ***b*** then node ***b*** is a neighbor of node ***a***, so each node is at most the neighbor of Δ other nodes and at each step of algorithm transmits at most Δ ***ACK*** messages to ***RTR*** messages of other nodes. The size of ***RTR*** and ***ACK*** messages depend on the ID size, which we do not include in computing the communication complexity.

According to above calculations, we can conclude that the communication complexity of our proposed algorithm for each node at each step is $\boldsymbol{O(\Delta)}$.

At each step each node must count the number of received ***ACK*** messages and compare it with the number of received ***ACK*** messages in the previous step. These actions take time $\boldsymbol{O(\Delta)}$, so the computational complexity of our proposed algorithm for each node at each step is $\boldsymbol{O(\Delta)}$.

A glance at Table 1 reveals a comparison of the computational and communication complexities of some transmission power control algorithms.

In the field of topology control, many of researchers do not include the step of determining the energy cost needed by each node to reach its neighbors in order to analyze communication and computational complexity. However, this step is the goal of transmission power control algorithms. And they assume that topology control algorithms begin with the assumption that each node can determine and will know the minimum power at which it should be transmitted in order to reach another specific node. Therefore, it is essential to include the energy cost estimation step in topology control algorithms to ensure that nodes can determine the minimum energy required for communication with their neighbors. This step helps to reduce energy consumption and prolong the network lifetime, as nodes can choose the optimal transmission power that balances the energy consumption and communication range. By considering the energy cost estimation step, topology control algorithms can effectively optimize network performance by controlling the communication topology. Furthermore, this step enables researchers to analyze communication and computational complexity, which is crucial for the design and evaluation of efficient and scalable topology control algorithms.

Table 1
A significant comparison between transmission power control Algorithms.

Algorithm name	Communication Complexity	Computational Complexity
LMA	$\boldsymbol{O(\Delta)}$	$\boldsymbol{O(\Delta)}$
LMN	$\boldsymbol{O(\Delta)}$	$\boldsymbol{O(\Delta)}$
TPC	$\boldsymbol{O(\Delta^2)}$	$\boldsymbol{O(\Delta^2)}$
STPC	$\boldsymbol{O(\Delta)}$	$\boldsymbol{O(\Delta)}$

By this assumption, we cannot compare the communication complexity and computational complexity of our method (and other transmission power control algorithms), with topology control algorithms. There are some complexity analysis for other steps (after the step of determining the energy cost each node needs to reach its neighbors) of topology control algorithms such as the analysis presented in Ref. [20].

6. Performance evaluation

As stated before, the proposed method is ***not*** a routing method, and it is a transmission power control method which could be used as a pre step of any routing method. So we do not compare our method with routing methods. Also we save all connections between nodes and do not change the graph which represent the topology of network, and just adjust the transmission ranges of nodes. So our method is different from traditional topology control methods, which change the topology of network. Thus, we do not compare our method with topology control methods.

In the field of transmission power control, the common approach used for evaluation of a proposed method is comparison of that method with max-power transmission method, for example in Ref. [5] which is a research just for analysis of transmission power control algorithms for wireless sensor networks, the proposed method is just compared with fixed-power (max-power) transmission method, also in Ref. [4] the proposed methods are compared with max-power transmission method.

The objective of the simulation is to compare the performance of our proposed method and the max-power transmission method in terms of energy consumption. Furthermore we compare the performance of our method with *LMA, LMN, TPC,* and *ATPC* based on the results reported in the [4,5].

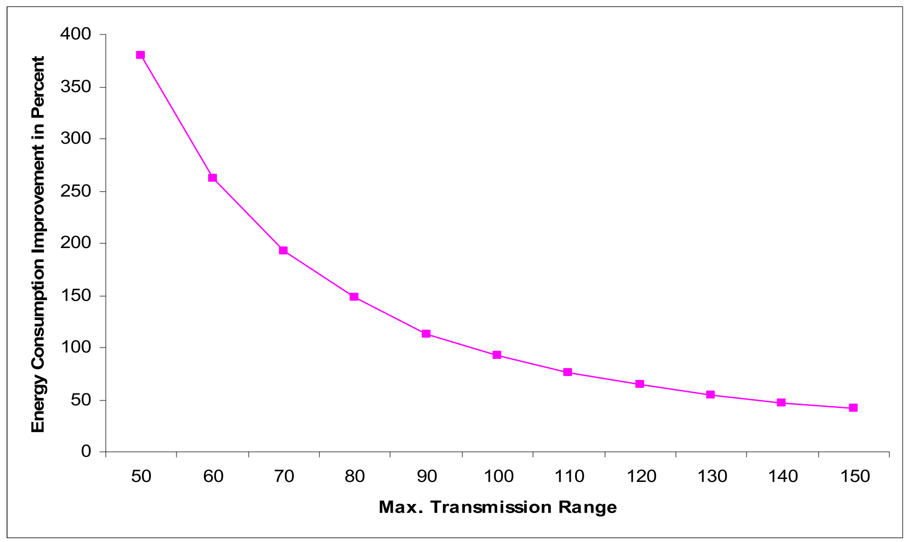
6.1. Simulation scenario

We have two simulation scenarios. In the first scenario ***100*** nodes are randomly deployed (using uniform probability distribution) in a ***1000 m * 1000 m*** region. The maximum transmission range ($\boldsymbol{R_c}$) varies from ***50 m*** to ***150 m***, number of steps of executed algorithm is **10** steps. The improvement in energy consumption is shown in Fig. 1(a).

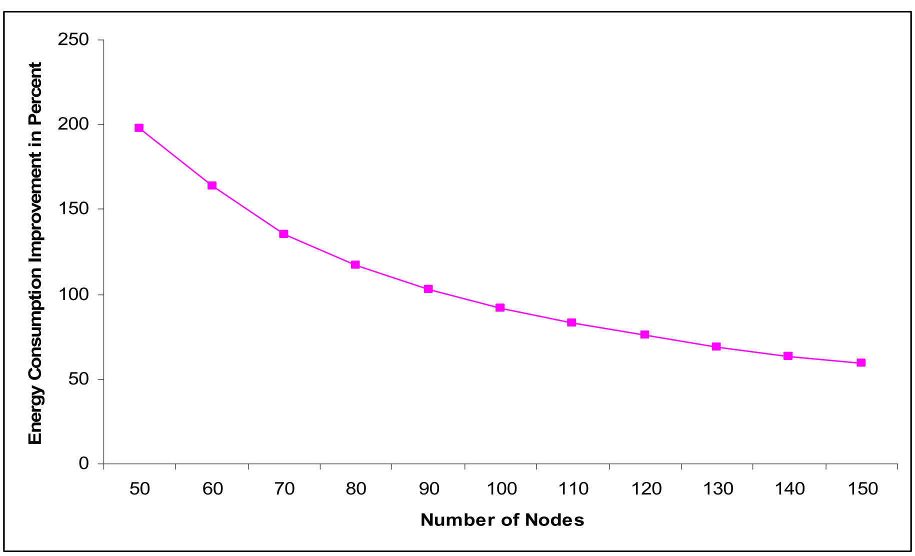
In the second scenario, ***50*** to ***150*** nodes are randomly deployed (using uniform probability distribution) in a ***1000 m * 1000 m*** region and the maximum transmission range ($\boldsymbol{R_c}$) is ***100 m***, number of steps of executed algorithm is **10** steps. The improvement in energy consumption is shown in Fig. 1(b).

6.2. Results and analysis

Fig. 1(a) and (b) show the energy consumption improvement of our algorithm with respect to a max-power transmission method. As we see in these Figures, there are two important parameters that affect the performance of our algorithm, Maximum Transmission Range and Number of Nodes. The algorithm has better performance in sparse environments with nodes that have shorter Maximum Transmission



(a)



(b)

Fig. 1. Energy consumption improvement; after each run of simulation, we calculate the new transmission ranges of nodes and calculate the energy consumption improvement for each node with respect to maximum transmission range. The average of these improvements for all nodes is the energy consumption improvement for this simulation run; each data point is an average of ***100*** simulation runs; (a) Variable maximum transmission range with constant number of nodes; (b) Variable number of nodes with constant maximum transmission range.

Ranges; this is expectable according to our theoretical calculations. For example in Fig. 1(a) if the Maximum Transmission Range is ***70*** m, in a ***1000 m*** * ***1000 m*** region with ***100*** nodes (which are deployed randomly using a uniform probability distribution), the expected number of neighbors of each node is less than 2 neighbor; in this case if we run our proposed method and set the transmission range of each node to value calculated by proposed method, according to our calculations the expected improvement factor in energy consumption for transmitting a message is about 1.75, which is verified by simulation results.

According to reports presented in Refs. [8–10], STPC (our proposed method) outperform all of proposed methods in that researches (*LMA, LMN, TPC* and *ATPC*) in sparse WSNs (WSNs with a few number of nodes with short Maximum Transmission Ranges deployed in a large area), in terms of energy consumption improvement, but the performance of other methods is better than *STPC* in some cases, none of these algorithms analyze the overheads of algorithms, furthermore it is not specified how to calculate the values of different thresholds used in the algorithm and in *ATPC* in the initialization phase of algorithm, each node needs global information about all of its neighbors. STPC outperform all of these methods in its targeted scenarios, while doesn't need magic threshold numbers or global information, furthermore its communication and computational overhead is less than or equal to these methods.

We must mention that, this comparison is not precise, because the simulation parameters are not equal in different reports, furthermore some simulation parameters are not reported. We compare the reported improvement of different methods in comparison with max-power transmission method, as we stated before the common approach is to compare the proposed transmission power control method with max-power transmission method.

7. Conclusions and future works

We studied the transmission range of sensors in wireless sensor networks in this study, and proposed a simple yet effective distributed transmission power control algorithm for sparse wireless sensor networks. We showed that this algorithm has advantages in many cases. The main idea of algorithm is simple, but performance of algorithm in targeted scenarios is excellent. We analyzed the performance of this method theoretically and show that using this method is worthwhile in some scenarios, especially in sparse wireless sensor networks with high amount of communication traffic. In these scenarios, our method can be used as a pre-step of any routing algorithm and decrease energy consumption and radio interference. As a future work, we intend to design methods to overcome the collisions problem. Designing methods for resisting the algorithm against the sensor failures is another future work. Furthermore we intend to work on using learning methods like Reinforcement learning for power control. Designing a good energy efficient reward mechanism is one of the main challenges of these methods.

Credit author statement

Seyed Hossein Khasteh:Conceptualization, Methodology, Data curation, Validation, Supervision, **Hamidreza Rokhsati**:Visualization, Data curation, Writing - Reviewing and Editing, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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