Extending Lifetime of Wireless Sensor Networks by Distributing the Overload on Cluster Heads

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Abstract: Clustering sensor nodes in power-constrained Wireless Sensor Network (WSN) is an efficient step to enhance energy efficiency and extend the network lifetime. Clustering gives many advantages (e.g., data aggregation and less number of transmissions) that greatly reduces the energy consumption of the WSN. A Cluster Head (CH) node is selected for each cluster to receive data from the cluster's nodes, aggregate them, and finally transmit these data to a Base Station (BS). However, the overhead on the CH nodes is still a problem for the network lifetime, which causes premature death for those overloaded nodes. Energy harvesting is one of the most energy optimization techniques that make the WSN rechargeable and so extends the lifetime of the network. Traditional techniques such as solar and wind harvesting are not reliable because they are neither constant nor always available. Another type of energy harvesting is the Wireless Power Transfer (WPT) approach in which a node enables to transfer energy to other nodes. According to the energy consumption theory in WSN, about 90% of energy is left unused after the premature death of overloaded nodes. If this big surplus of energy is used to recharge the overloaded nodes, it will greatly extend the lifetime of the WSN. So, in this paper, we use the WPT technology and the multi-objective Particle Swarm Optimization (PSO) to extend the network lifetime. The target of our proposed approach is to minimize the amount of this surplus of energy. All nodes in the WSN could transfer energy to the CH nodes to distribute the overall load. At the same time, the optimal amount of energy, transferred by each node, must also be convenient to its residual energy. Therefore, this paper tries to eliminate the overhead on the CH nodes and therefore extend the lifetime of the clustered WSN. Our simulation results show an encouraging result to extend the lifetime of the WSNs as compared with the common Leach algorithm.

1 INTRODUCTION

WSN is one of the most effective factors that have achieved recent smarting and technological progress in many vital fields such as healthcare, military, and smart cities (Yang et al., 2015; Wu et al., 2018). WSN consists of a set of small, cheap, and smart devices called sensor nodes. Each sensor node is responsible for three main tasks: sensing an interesting area, processing the sensed data, and finally transmitting the interesting events to the BS in order to take the convenient actions remotely. Each sensor node is powered by a limited capacity battery, which makes the WSN power-constrained and with a limited lifetime. This will, in turn, has a negative effect on the availability and the performance of this efficient technology. Many energy optimization techniques have been proposed to extend the lifetime of the WSN. One of the most energy-efficient approaches is a clustering step in which sensor nodes are grouped into clusters, where each cluster has a cluster head (CH) node (Arghavani et al., 2017). In each data transmission round, a sensor node transmits the sensed data to its CH node, which aggregates the sensed data of all its cluster members in one data packets (data aggregation) and finally transmits the aggregated data to a BS. A clustering approach has achieved many features that not only greatly extend the lifetime of the WSN, such as data aggregation and less number of transmission which greatly reduce the communication overhead, but also improve the performance and throughput of the WSN. This improvement will be done by ensuring the connectivity between the nodes and the BS, facilitating the security for the whole WSN by securing only the CH nodes rather than all nodes in

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the network (the CH nodes are considered as gateways for the network) and finally provide scalability for the WSN (Afsar et al., 2014). However, all clustering approaches have a common dangerous problem which is the huge overhead on the cluster head (CH) nodes (Kuila et al., 2013) as CH nodes are responsible for receiving data from all their cluster members, aggregating them and finally transmitting the aggregated data to the base station (BS). Therefore, the CH nodes are exposed to huge energy consumption, which causes premature death for the nodes and harms the lifetime of the WSN.

Energy harvesting is one of the hot approaches to recharge the batteries of the sensor nodes from other energy sources. Traditional energy harvesting approaches convert the energy from natural sources, such as solar or wind harvesting, into electric energy to replenish the energy of the sensor nodes. However, traditional energy harvesting is not reliable because it depends on the current environmental conditions that are not constant or always available. Another energy harvesting approach is WPT, by which the nodes can exchange energy with each other to recharge their batteries. Based on the energy consumption theory, at the same time, when the first node depletes its energy, 90% of the initial energy in the network still exists (Yu et al., 2018). So in this paper, we propose to use this big surplus of energy as a source to replenish the battery of the overloaded nodes, using WPT, and so extend the lifetime of the WSN. Practically, each node intends to keep its residual energy large as much as possible to be able to perform its assigned tasks, but at the same time, it should transfer an amount of energy to the overloaded CH nodes, to increase the lifetime of the WSN, which is considered as a multi-objective optimization problem. Therefore, we use a particle swarm optimization algorithm to determine the optimal amount of energy to be transferred from each node to reduce the overhead on the CH nodes. At the same time, the amount of energy transferred does not harm the lifetime of the source nodes.

Software-defined network (open flow) is a recent approach in networking where the control is decentralized from the data plane and embedded in a device called controller (Kobo et al., 2017). Open flow is used here to choose the optimal route for the power transfer.

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

- We eliminate the centralized overhead on the CH nodes, which exists in the traditional clustering algorithm, by distributing the load over all nodes in the network. The target of our proposed approach is to minimize the number of energy surpluses at the time of premature network death (i.e., extend the lifetime of the network).
- To the best of our knowledge, no prior work tries to use the WPT technology and the multi-objectives particle swarm optimization to extend the network lifetime.
- At the same time, we conserve the topology of the clustered sensor nodes which achieve the pre-discussed energy-efficient features.
- Our approach does not require any external energy source, which is costly and not suitable for all WSN applications such as healthcare to recharge the nodes.

The rest of this paper is organized as follows. Section 2 covers the related works. The system model is described in Section 3. We explain the proposed algorithm in Section 4. The performance and evaluation of the proposed algorithm are analyzed in section 5. Finally, Section 6 concludes our work.

2 RELATED WORKS

Many clustering algorithms have been proposed to extend the lifetime of the WSN. Leach algorithm is one of the most common clustering algorithms in which the CH nodes are selected randomly (Heinzelman et al., 2000). Whereas each node firstly generates a random value between 0 and 1, and then if the generated value is less than a predefined value, this node is selected as CH node. The other nodes assign to the nearest CH node. Leach has some drawbacks because the nodes with less residual energy may be selected as CH nodes, and this causes premature death for them. Also, the CH node communicates directly with the BS, and this causes a huge communication overhead. The unequal clusters that often formed by the traditional clustering algorithms make the load of the CH nodes unbalanced. The smaller the number of nodes in a cluster, the less load of the CH for this cluster.

According to (Zhao et al., 2018), each node initially generates a cluster that includes itself. After that, the generated cluster iteratively merges with the nearest neighboring cluster until a predefined number of clusters is reached. The distance between two clusters can be calculated by the longest distance between any two nodes or the shortest distance between any two nodes in the two clusters. The CH nodes must have higher residual energy, closer to the center of the cluster, and closer to the BS. The algorithm differentiates between large and small cluster sizes to balance the load between all CH nodes. It considers the cluster whose energy consumption more than 1.5 of the average energy consumption for all clusters as a large cluster. Therefore, the cluster head role in large clusters is performed by two CH nodes: secondary CH node, which is responsible for receiving the sensed data from all cluster members, aggregating them and transmitting them to the primary CH node, which is responsible for transmitting the aggregated data to the BS. So, the load is reduced and balanced between the CH nodes in either large or small clusters. However, the algorithm requires computation and time overhead in the merge process to change the number of clusters from the number of nodes (initially) to the predefined number of clusters. Also, using two CH nodes in many clusters increase the number of overloaded nodes, and this harms the lifetime of the WSN. Generally, reducing the load on the CH nodes by rotating the CH role or balancing the load between CH nodes is efficient but not optimal solution because in the usual case the CH node is overloaded because of the nature of its role and this cause energy consumption for the CH nodes and this cause premature death for them (Yadav et al., 2017).

3 SYSTEM MODEL

We consider a network of n sensor nodes that are distributed randomly in an interesting area and a BS, which is located in the middle of this area. Each sensor node is powered by a rechargeable battery. Also, let each sensor node supports the open flow protocol, and the controller is embedded in the BS. Each node is assumed to have a unique ID value, and it supports the wireless power transfer capability. In order to achieve the most efficient power transfer, we use an approach called "strong resonant coupling" to transfer power between the source and the destination nodes. Strong resonant coupling is considered as one of the best WPT approaches regarding the transmission range and the transmission efficiency (Menon et al., 2013). We use the same radio model for energy as in (Heinzelman and W.B, 2000). The energy consumption for transmitting l bits a distance d is calculated using equation 1.

$$E_{T_x}(l,d) = \begin{cases} l\,E_{elec} + l\,\varepsilon_{fs}\,d^2 & \text{for } d \le d^o \\ l\,E_{elec} + l\,\varepsilon_{mp}\,d^4 & \text{for } d > d^o \end{cases} \quad (1)$$

Where E_{T_x} is the consumed energy for transmitting l bits for distance d, E_{elec} is the energy required by the electronics circuit, ε_{fs}, and ε_{mp} are the energy required by the amplifier in the free space and the multipath, respectively. The energy consumed for receiving l bits can be calculated by equation 2.

$$E_R(l) = l \times E_{elec} \quad (2)$$

4 THE PROPOSED APPROACH

The proposed approach to extending the lifetime of a WSN has two main steps: clustering and optimization. Initially, in the first step, clusters are formed according to the Leach algorithm (Heinzelman et al., 2000). Each node will generate a random number between 0 and 1. If the generated value is less than a predefined threshold, the node is considered as a CH. After that, each node transmits its status (residual energy, location, and whether it is a CH or not) to the controller. Therefore, the controller has a global view of the whole network (network map), and so it can implement the proposed optimization algorithm. Our proposed optimization algorithm, which shall be discussed in the next subsection, determines the optimal amount of energy that will be transferred from each node to compensate for the overloaded CH nodes. The controller then submits to each node the ID of its corresponding CH, the amount of energy which the node can transmit to the overloaded CH nodes through the network, and the best routes for the energy transfer.

4.1 PSO Algorithm

PSO is a heuristic-based computational algorithm inspired by birds flock which searches for food location. The candidate solution, in PSO, is called a particle. Each particle has two parameters: location and velocity. By them, the particle moves through the search space towards an optimal solution. PSO is an iterative algorithm. In each iteration, it evaluates the particle position using a fitness function and records the optimal local value of the particle and the optimal global value for all particles. Using the local and global optimal values, it calculates the updated velocity, which is used to know a new location of the particle (new candidate solution). The velocity and location of the particle are updated using equations 3 and 4, respectively.

$$v_i(t) = \omega v_i(t-1) + c_1\varphi_1(t-1)[P_i(t-1) - x_i(t-1)] + c_2\varphi_2(t-1)[gb(t-1) - x_i(t-1)] \quad (3)$$

$$x_i(t) = x_i(t-1) + v_i(t) \quad (4)$$

Where $v_i(t)$ is the velocity of particle i at round t, $x_i(t)$ is the position of particle i at round t , c_1 and

c_2 are two positive constants, P_i is the local best of the particle i, gb is the global best of all particles, φ_1 and φ_2 are two random number between [0,1]. The PSO algorithm has different advantages: ease of implementation, efficient solution, and computational and memory efficiency usage.

4.2 PSO-Based Power Transfer

The global view of the controller to the whole network allows it to determine the CH for each node easily and to calculate the load assigned to all nodes (CH nodes/member nodes). Using the PSO algorithm, the controller will determine the optimal amount of energy needed to be transferred to the CH nodes to compensate for their overload. For distributing the CH overload over the nodes, there are two possible approaches. First, the overload of the CH node in a cluster is locally distributed over the member nodes of this cluster only. Second, the overall CHs overloads in the network are globally distributed over all nodes in the WSN. In most clustering algorithms, we can observe that CHs close to the BS bear a huge load than the CHs away from the BS. Therefore according to the first approach for the clusters near the BS, member nodes in such overloaded clusters are likely forced to transfer a big amount of energy even if their residual energy is not sufficient, which is not efficient for their lifetime. Although, at the same time, there may be other nodes (almost have higher energy) that transfer a small amount of energy because of the less overload on their CHs. So, the second approach is more efficient because it balances this overload on all nodes in the network. Therefore, the dimension of the particle/solution here is equal to the number of nodes in the network. Each value corresponds to the possible amount of energy that could be transferred from each node in the network to eliminate the overall CHs Loads.

4.2.1 PSO Fitness function

Our optimization problem has two basic objective/fitness functions f_1 and f_2 that aimed to characterize the optimal amount of energy. The first function allows each node to transfer an amount of energy, which is suitable to its residual energy (i.e., the more residual energy of a node the larger amount of energy to be transferred). The function f_1 can be calculated as in equation 5.

$$f_1 = Min\left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{E_i}{\sum_{j=1}^{n}E_j} - \frac{E_{Trs_i}}{\sum_{j=1}^{n}E_{Trs_j}}\right|\right) \qquad (5)$$

Where n is the number of nodes, E_i is the residual energy of the node i, E_{Trs_i} is the amount of the transferred energy from the node i. When the value of f_1 is small, this means that the ratio of the energy of the node to the energy of all other nodes (the first modulus term) is approximately equal to the ratio between the amount of transferred energy from the node to transferred energy from all other nodes (the second modulus term). This means the node will transfer an amount of energy which is suitable to its residual energy. In other words, when residual energy is high as compared to the energy of other nodes, the node is supposed to transfer a larger amount of energy than the transferred energy by these other nodes and vice versa.

The second objective function considers other loads for a node, such as data transmissions and sensing. For example, there may be a case in which two nodes have an equal or close amount of energy, but the load on one of them is large as compared to the second node. So, it will not be fair to transfer the same amount of energy from the two nodes. This function tries to maximize the minimal residual energy over the whole nodes after the process of energy transfer. The function f_2 is calculated using equation 6.

$$f_2 = Max\left(\min\left(E_i - \left(Load_i + E_{Trs_i}\right)\right)\right) \quad (6)$$

Where E_i is the residual energy of the node, E_{Trs_i} is the amount of the transferred energy from the node, and $Load_i$ is the load assigned to the node i. Therefore, the algorithm considers both the energy of the node and the load of the other tasks assigned to the node in order to extend the lifetime of the source node. We can observe that the two objective functions are in conflict. Our optimization problem has a constraint that the sum of the transferred energy from all nodes must be equal to the overall load on all CH nodes in the network. That is:

$$\sum_{i=1}^{n} E_{Trs_i} = \sum_{j=1}^{m} CH\_L$$

Where CH_L is a load of a CH node, and m is the number of CH nodes in the network. Most bio-inspired optimization algorithms are applied for unconstrained-optimization problems. So, we will use an efficient and common constraint handling technique, which is a penalty function. Penalty function converts the constrained optimization problem into an unconstrained optimization problem which can be solved by a bio-inspired optimization algorithm easily. This is done by adding a term, called "quadratic loss function," to the objective function and converting the constraint to an objective in the objective function. So the adjusted objective function becomes:

$$f_2' = \alpha f_1 + (1-\alpha)\frac{1}{f_2} + C\left(\sum_{i=1}^{n} E_{Trs_i} - \sum_{j=1}^{m} CH\_L\right)^2$$

Quadratic loss function becomes squared to make the constraint more severe to be applied. C is a constant, and its value is ranged from 10 to 100, and α is a weight value.

Therefore, the overload of the CH nodes in the network is completely distributed over all nodes. So, this huge load is divided into smaller loads (because of the big number of nodes that bear this load together) and be assigned to the whole nodes in the network based on the node energy and the other task loads.

4.2.2 Energy Transfer and Delay Reduction

After the algorithm determines the optimal amount of energy that needs to be transferred from each node, the controller submits an MSG to each node, which contains its CH id, the amount of energy required, and the optimal route for the energy transferring. There are two main approaches in power transfer: a single-hop approach in which the energy is transmitted directly from the source to the destination, where there are no intermediate nodes, and a multi-hops approach in which the energy is transmitted hop by hop (passing through multiple nodes) from the source to the destination. Generally, the energy transfer process is affected by the distance between the nodes (Han et al., 2018). The longer distance between the source and destination, the less energy transfer efficiency is achieved. Also, there exists a limited distance value, after which the receiver cannot receive any amount of energy (exceeds the power transmission range). We can observe that the multi-hops approach is more efficient than the single-hop because it can extend the transmission range where a source can transmit energy to another node, which is not in its transmission range. Also, the multi-hops approach improves the transfer efficiency because the distance between the source and any intermediate node is less than the distance between the source and the destination. The energy is transferred with the shortest path, determined by the global view feature of the controller, in the multi-hops approach. Numerous studies have been conducted to demonstrate that using a resonant repeater (inside each sensor node) to achieve energy transmission is the most effective method (Han et al., 2018). Also, the repeater improves the strength of the wave and compensates for any loss during transmission. So, the repeater with the shortest path generated by the global view is used to guarantee the best energy transmission efficiency. Each CH harvests an amount of energy equals the load of its CH role.

Our proposed algorithm uses the "simultaneous energy transmissions" mechanism to reduce the delay in the case where the transferring node is far from the target CH node (not in its cluster). Whereas, if the CH, after harvesting energy from its cluster members, still needs an extra amount of energy to eliminate its assigned CH load completely, the controller chooses the nearest set of nodes whose residual energy allows to transfer the extra amount of energy to the CH node. In this way, this set of nodes will transfer an amount of energy larger than its optimal amount, which is determined by the algorithm. The controller then chooses another set of nodes that is nearest to the first set to compensate for the extra load of the first set (second level). Iteratively, this power transfer process is repeated level by level simultaneously until reaching the nodes that are supposed to transfer energy to the far CH node from them. So, the far node logically transfers energy for the CH node at the same time the closer node to the CH node, and so delay is reduced.

5 PERFORMANCE EVALUATION

We simulate our proposed algorithm under Matlab. The performance is compared with the Leach algorithm in terms of network lifetime and the elimination of the CH load. We apply our algorithm in a network consists of 100 nodes and distributed randomly in 100×100 meters, as shown in Figure 1.

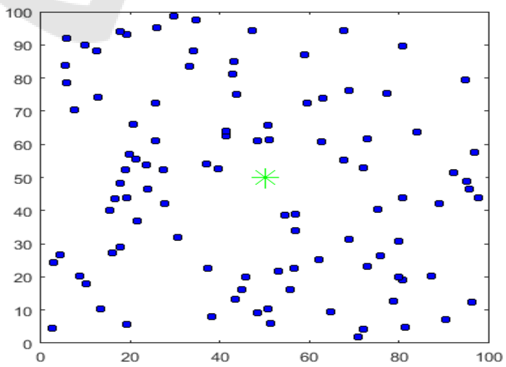

Figure 1: A simulated network distribution.

The BS is located at the center of the network (50, 50) to achieve the best performance. The simulation parameters and values are listed in Table 1.

Table 1: This caption has one line, so it is centered.

Parameter	Value
Network size	100 × 100
Nodes number	100
BS position	(50,50)
Data packet size (bits)	4000
Control packet size (bits)	100
Initial node energy (J)	0.1
Transmission range (m)	20
C1	1.5
C2	2.0
W	1
C	10-100

Generally, the optimal solution of the PSO is based on the number of particles and the number of iterations. So, we ran the algorithm many times with different values for the two parameters and found that the best value has occurred when the number of particles equals 200, and the number of iterations equals 2000, as shown in Figure 2.

Compared to the Leach algorithm, our algorithm shows an efficient extension for the lifetime of the wireless sensor networks. The first node in Leach is died at around 284, but in our algorithm, the first node is died at around 350. Also, in Leach, the last node has died at around 315, but in our proposed algorithm, the last node died at around 400, as shown in Figure 3. This extension of life occurs because the huge overhead on the cluster head nodes is efficiently eliminated and distributed over the whole nodes. By dividing this overhead over a big number of nodes, there are no overloaded nodes, and also the average energy consumption of the CH nodes is approximately equal to the average energy consumption for ordinary member nodes in around as shown in Figure 4. This will enhance the energy efficiency of the clustering algorithms, whereas the centralized overhead on the CH nodes is distributed over the whole nodes.

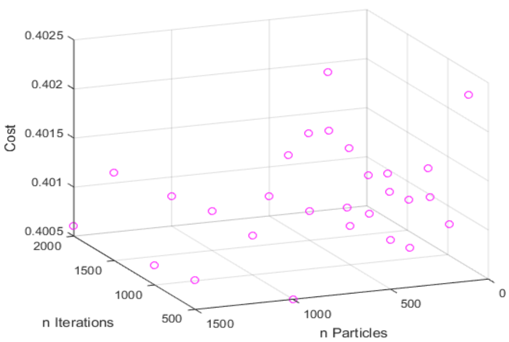

Figure 2: The best cost based on a different number of particles and iterations.

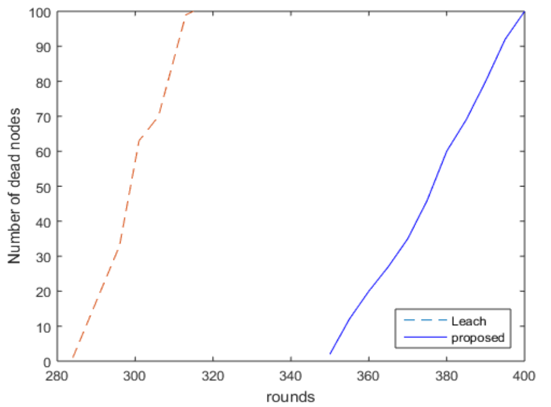

Figure 3: Lifetime extension for the proposed algorithm is compared to Leach algorithm

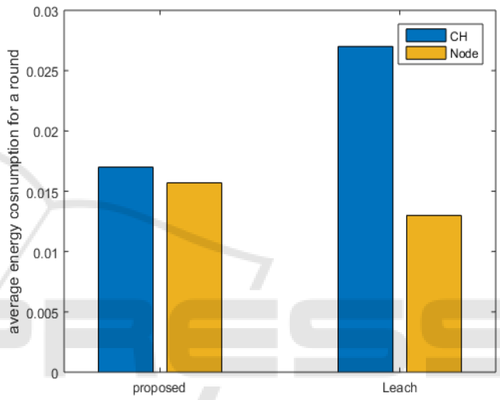

Figure 4: Elimination of CH nodes overhead in the proposed algorithm is compared to the Leach algorithm.

6 CONCLUSIONS

In this paper, we eliminate the centralized overhead on the CH nodes by integrating the WPT and PSO algorithm, where each node can transfer an amount of energy, determined by the PSO model, to the overloaded CH nodes. Therefore, this huge load is divided into small values and distributed over the whole nodes based on their residual energy and load. Although our algorithm eliminates the centralized CH load, it keeps on the clustered topology, which provides energy-efficient features for extending the lifetime of the WSN. We plan to apply other optimization algorithms and compare them with the PSO algorithm on other simulated networks.

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