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Energy-Efficient Link-aware PSO-Based Clustering Algorithm in Wireless Sensor Networks (WSNs)

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ABSTRACT: Recently Wireless Sensor Networks (WSNs) has turned into a popular matter of research area, because of its flexibility and dynamic nature. It is proven that the clustering technique, as a multi objective optimization, is the most effective solution to have minimum energy consumption. The goal of the clustering technique is to divide network sensors into clusters each of which has a cluster-head (CH) responsible to collect, aggregate and send sensed data to the base station (BS). The recent researches shown that such multi objective optimization in WSNs can be solved through well adapted an evolutionary algorithm. In this paper an improved k-mean clustering model powered by Particle Swarm Optimization (PSO) algorithm is presented. This is called Link-aware PSO, LSPO. The proposed model utilizes two-phase optimization by applying different fitness function. At the first phase, it selects Primary Cluster-heads based on improved Intra-Cluster Distance metric as fitness function in PSO algorithm to give primary CHs. In the second phase each primary CHs selected are evaluated by link quality and energy metrics to select the best ones as final CHs. Simulation results showed that the proposed algorithm outperforms LEACH and PSO-C algorithms in term of performance, prolonging network lifetime and energy saving.

KEYWORDS: Wireless Sensor Networks (WSNs), Clustering, Particle Swarm Optimization, Energy Efficiency, Link Reliability.

1 INTRODUCTION

A Wireless Sensor Networks (WSNs) is a dynamic and self-adapting network in which sensor nodes send their information to a base station (sink). It has a set of dynamic sensor nodes that can move freely. These nodes have limited processing speed, battery, storage, and communication capabilities. These features lead to some inefficient states, so it needs a set of new area in researches to solve or smooth this problem. One of solutions is clustering, in which a network is divided into some zones called clusters. Each cluster has a cluster head (CH) and each node as soon as finding the most appropriate CH, will join the CH and will form a cluster. CHs are responsible for the formation of clusters, maintenance of network topology, allocating resources to all nodes belonging to their clusters and sending the members' data to different destinations (Routing). Because of limitation of energy and dynamic nature of WSNs and varied quality of link between CHs and their members, CHs constantly need to be changed. Based on [1], An optimal selection of CHs is an NP-hard problem. In addition, Energy and Link quality metrics play very important roles in this area, and increase network lifetime and efficiency. So clustering needs to be combined with some optimization approaches to improve performance of CH selection. Clustering optimization refers to finding one or more solutions, which satisfies the goal of selecting a set of CHs which are recognized the best after evaluation based on metrics such as intra-cluster distance, energy-efficiency and link-quality. It has been an active research area as many real world optimization problems, referred to as multi-objective problems (MOPs) have recently been proposed. Therefore it is needed to choose the most appropriate approach which satisfies the optimization factors and because of that the network can last more while. There are some traditional problems which generate a single solution from the set of solutions in one run, so they are just appropriate for Single-Objective Problems (SOPs). Based on[1]–[3], these problems are not suitable for solving MOPs. Among them the most suitable way is Evolutionary algorithms, because they are population-based and due to conflicting objectives they can and need to generate a set of solutions in one run.

In this paper we introduce a multi-objective two-phase Particle Swarm Optimization referred to as Link-aware PSO (LPSO). The fitness function in this paper includes two phases. In the first phase Primary CHs (PCHs) are selected based on metrics Intra-cluster distance and distance between CHs and the sink. At the second phase these primary CHs and their members are re-evaluated again based on metrics such as Link Quality and Energy, then the best nodes will be considered as Alternative CHs (ACHs). The proposed algorithm because of the minimum distance between CHs and their members and considering energy-efficiency and link quality can be more effective than other well-known algorithms: Low-Energy Adaptive Clustering Hierarchy (LEACH) [4], [5] and PSO-Centralized (PSO-C) [6]. Experimental results show that proposed algorithm outperforms energy and link quality effectiveness, network life time and preserving energy for longer time.

The rest of the paper is organized as follows: In section 2 we will give an overview of the previous PSO and Evolutionary based clustering algorithms. Section 3 describes PSO Algorithm principles. Section 4 provides an overview of proposed LPSO clustering algorithm and finally in section 5 and 6 experimental results and future work will be mentioned.

2 RELATED WORKS

In [7]–[9] Genetic Algorithm was used to optimize the number of the number of clusters in an ad hoc network. It is a weight based clustering algorithm, which assigns a weight to each objective of the problem and is set by the user. In [10] Enhanced PSO-based Clustering Energy Optimization (EPSO-CEO) is introduced. This algorithm tries to Minimize energy consumption by straight transmission of data from each node to its CH. CHs are selected based on Energy consumption rate of nodes. In [11], for minimizing early death rate of nodes and balancing energy consumption between all sensor nodes, a combination of PSO and Taguchi is proposed. For maximizing factors such as performance, energy consumption balance, link quality, network coverage [12] proposed Two-Tier PSO-Clustering and Routing (TPSO-CR). In proposed algorithm just nodes with high level of energy of energy can participate in clustering and routing activities.

The author of [12], in [13] proposed PSO-Hierarchical Clustering (PSO-HC). The purposed of this algorithm is to maximize lifetime and scalability of network and minimize number of active nodes during each round and the energy dissipated by their activity. Fitness function acts based on residual energy and number of neighbors of each node (node's degree). Authors of [14] proposed Particle Swarm Optimization – Double (Cluster) Head (PSO-DH) which is inspired by LEACH algorithm. Purpose of this algorithm is to minimize intra-cluster distance and optimize energy consumption of nodes. This algorithm provides two kinds of CH nodes: Master CH (MCH) and Slave CH (SCH). The MCH aggregates data from members and SCH sends aggregated data to the sink and by reducing the level of MCH's duties, considerable energy is saved.

In this paper the proposed algorithm finds the optimum set of cluster-heads in two phases based on link quality, energy effectiveness, improved intra-cluster distance (minimum distance between CHs and their members inside each cluster).

3 PROPOSED LPSO METHODOLOGY

PSO introduced by [15]–[18], is a kind of Evolutionary Optimization Approach which inspires from life of swarms of birds or living creatures finding an area to achieve a common goal. PSO includes some of individuals known as Particles, which explore an n-dimensional search area, in the aim of finding a solution for a problem.

This solution depends on some objectives such as energy level and so on. PSO algorithm includes some parameters such as particle position and velocity (bounded by a value V_{max}) (determining the direction of individual for exploring the area), Personal Best and Global Best. Personal and Global best (as minimum of all personal bests) are defined in order as each individual's and the individual's neighbors' best ever found solution. After moving each particle in the search area (by updating their position and velocity), each particle is evaluated and then global and personal best values will be updated. For several iterations these processes are repeated, until finding a solution for the problem.

As [18] claims, one of the common problems in PSO is referred to as Explosion Problem. In this problem sometimes growing values of position and velocity is out of control and their values approach toward infinity. So the particles will be thrown outside the search area and invalid answers will be produced. For avoiding this problem, the proposed algorithm uses the idea mentioned in [18].

In the search process the particles adjust their positions according to the following equations (1) and (2):

$$V_{i,j}(t+1) = \chi . [\, \varpi_{max} . V_{i,j} + r_{1,j}\left(P_{i,j} - X_{i,j}(t)\right) + r_{2,j}\left(G_j - X_{i,j}(t)\right)] \tag{1}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{2}$$

Where i indexes the current generation, c_1 and c_2 are positive constants, r_1 and r_2 are random numbers with uniform distribution on the interval [0,1]. A commonly used parameter that changes the original PSO is the Constriction Coefficient which is defined as following equation (3):

$$\chi = \frac{2}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|}\left(Where: \quad \varphi = c_1 + c_2 \quad , \varphi > 4\right) \tag{3}$$

This coefficient introduced first by Clerc et al. in [17], guarantees the algorithm convergence, avoiding the explosion of the particle swarm (approaching velocity and position towards infinity). Another parameter is the inertia weight that is:

$$\varpi = \varpi_{max} - \frac{\varpi_{max}-\varpi_{min}}{F_{max}} F_k \tag{4}$$

This parameter guarantees the balance between local and global best. A higher value (greater than one) will facilitate the exploration, while a low weight (less than one) will facilitate the exploitation. The wrong choice of this parameter value will affect the algorithm convergence speed, so it is recommended to adjust it dynamically by equation (4). At first phase each of the particles (here the mobile nodes) is evaluated using following equation (5):

$$f_1 = \sum_{j=1}^{k} \sum_{i=1}^{n_j} d_{ij}^2 + \frac{D_j^2}{n_j} \tag{5}$$

After evaluation of nodes by equation (5), nodes having minimum values of distance will be elected as Primary CHs. Finally normal nodes will join the closest CH and will establish a cluster structure. In the second phase, the primary CHs and their member will be compared to each other based on the factors link quality (f_3), residual energy (E_i^{res}) and consumed energy (E^{tx}) as equations (6) to (9) introduce. The best nodes satisfying the optimum value of the greedy function will be selected as the Alternative CHs. Figure (1) briefly describes steps of proposed algorithm in a flowchart.

$$f_2 = \frac{E_i^{res}}{\sum_{i=1}^{n_i} E^{tx}(k,d_{ij})} \qquad (for\ each\ node_i\ in\ \ cluster_j) \tag{6}$$

$$E^{tx}(k,d_{ij}) = \begin{cases} k\,.E_{elec} + k.\epsilon_{fs}.d_{ij}^2 d_{ij} < d_0 \\ k.E_{elec} + k.\epsilon_{mp}.d_{ij}^4 d_{ij} \geq d_0 \end{cases} \tag{7}$$

$$f_3 = \sum_{i=1}^{n_j} d_{ij}^2 \qquad (for\ each\ node_i\ in\ \ cluster_j) \tag{8}$$

$$Greedy\ Function = \frac{f_2}{f_3} \tag{9}$$

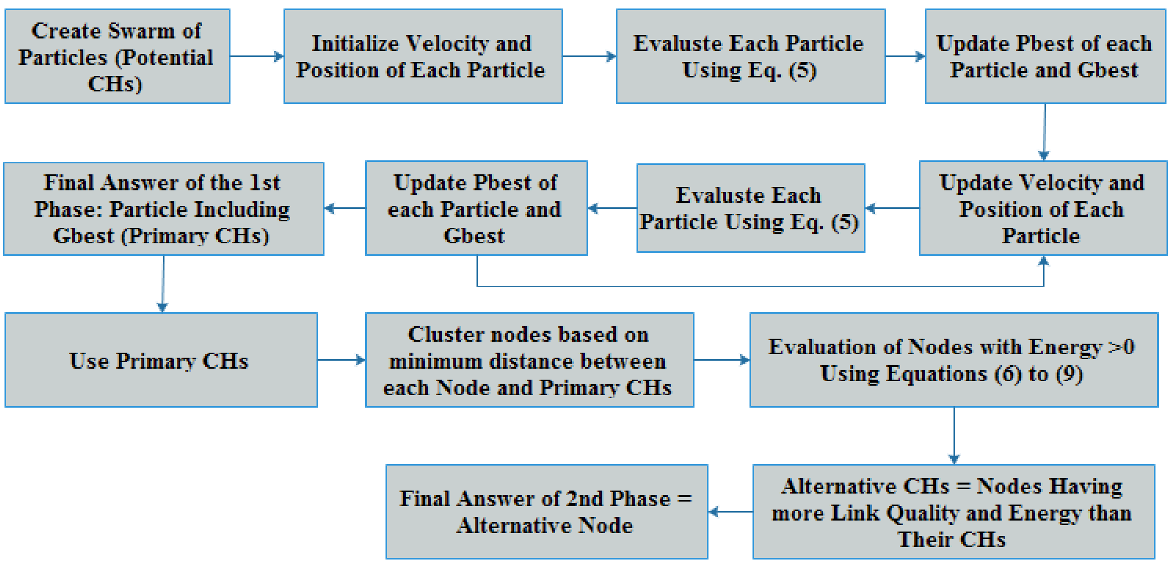

Figure1. Flowchart of proposed LPSO Algorithm

4 EXPERIMENTAL SETUP AND RESULTS

The proposed algorithm is implemented under the in table 1. Also Simulations compare proposed LPSO with algorithms known as LEACH and PSO-C with the parameters shown in table 2.Table 3 contains some statistics about result of program. The following table compares the functionality of proposed algorithm with LEACH and PSO-C in terms of death time of the first and last node and average dissipated energy per round.

Figure 1 shows a random layout of the nodes within the network area of 100 meter squares and the sink located outside the area. The proposed technique chooses CHs based on link quality, residual energy, transmission power, distance of each CH from the sink and distance of nodes from each other, with the selected CHs at the center of each cluster. As seen, proposed algorithm organizes the network as some clusters based on the factors determined by fitness function and uses a multi-hop routing protocol for sending data to the sink. Data transmission and routing approaches is the same in all compared algorithms. The red line shows the route from each CH to the Base Station.

As Figure 2 shows, after interaction between different nodes and losing energy during lifetime of network, nodes will be gradually weaker and finally will be eliminated. Briefly, the more nodes are alive, the longer lifetime and stability of network will last. However, it is considerable that the longer the process of elimination and death of nodes last, the shorter period of time the network will survive. So for maximizing performance and efficiency and lifetime of network and losing the first node at later time, getting aid from an optimization algorithm is crucial. Figure 3 shows the gradual progress of energy dissipation of network nodes due to interaction between nodes. As it is evident in figure 4 by using proposed approach, energy is dissipated in a longer period of time and is preserved for a longer time. The energy management acquired in proposed LPSO leads to more number of nodes being alive as shown in Figure 5.

Table1. System Specifications for Running Program

Processor	Intel Pentium, Core-2
Random Access Memory	1-GB RAM
Cache	1M Cache
Hard disk	512 GB HDD
Programming Language	Matlab

Table2. Initializations and input values Needed for Running Program

Initial energy for each node	0.5(Joule)
Field size	100 x 100 (Meter)
Base Station	Random out of border
Network size	100 , 200,400
Maximum number of CHs	5
Simulation time	6000(Second)
Number of Particle (PSO)	100
Number of Iterations	20
Position and Velocity Vectors	5x2 Arrays
Acceleration Coefficients	$c_1 = 1.85$, $c_2 = 2.20$
Inertia Weight Damping Ratio	0.95

Table3. Statistics about functionality of proposed LPSO in comparison with LEACH and PSO-C

Proposed LPSO	**PSO-C**	**LEACH**	
123	305	639	**Death of the first node**
1354	1233	1139	**Death of the Last Node**
1231	928	500	**Difference of first and last node death time**
0.0406 (Joule)	0.0446 (Joule)	0.0495 (Joule)	**Average dissipated energy per round**
3193(s)	3153(s)	339 (s)	**Total Running time**

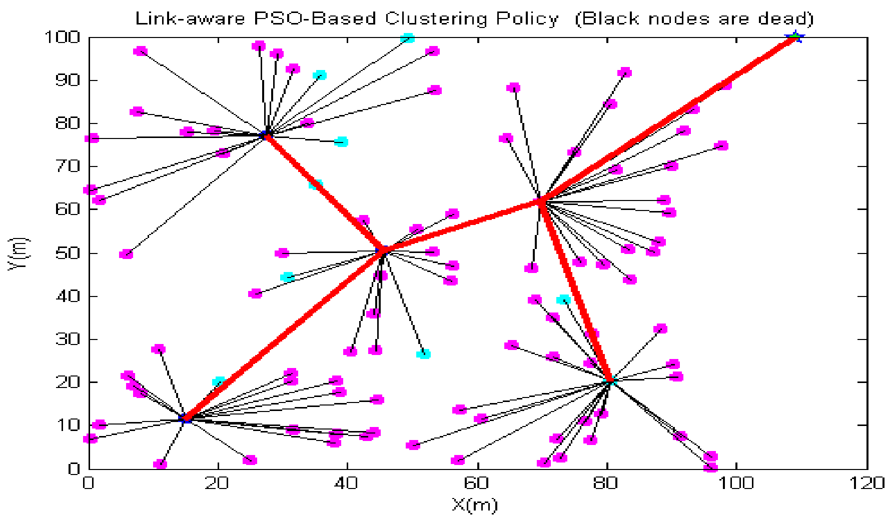

Figure1. A schematic symbol of running program

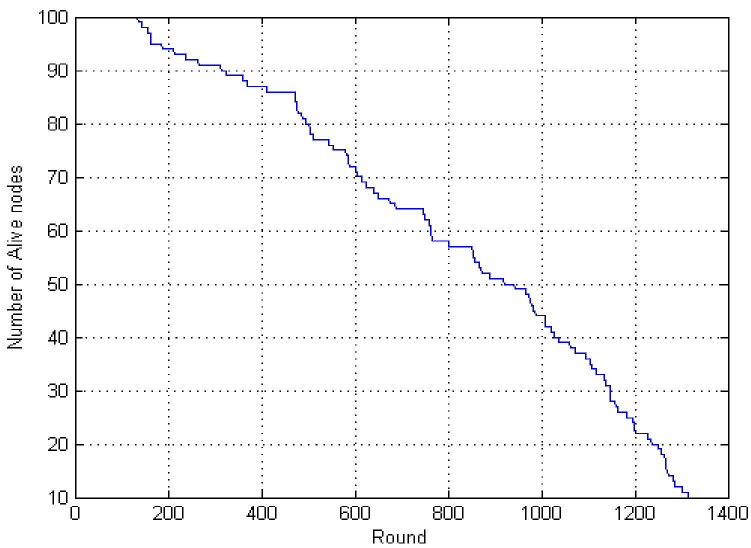

Figure2. Nodes gradually lose energy during network lifetime and will be dead

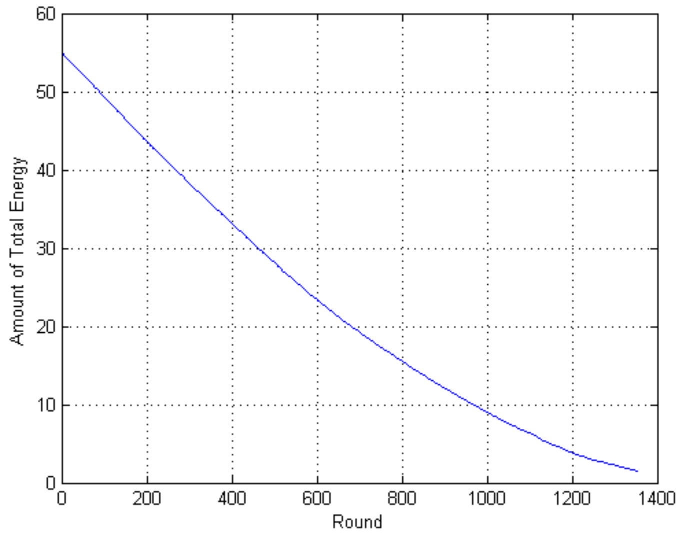

Figure3. Energy dissipated during network lifetime

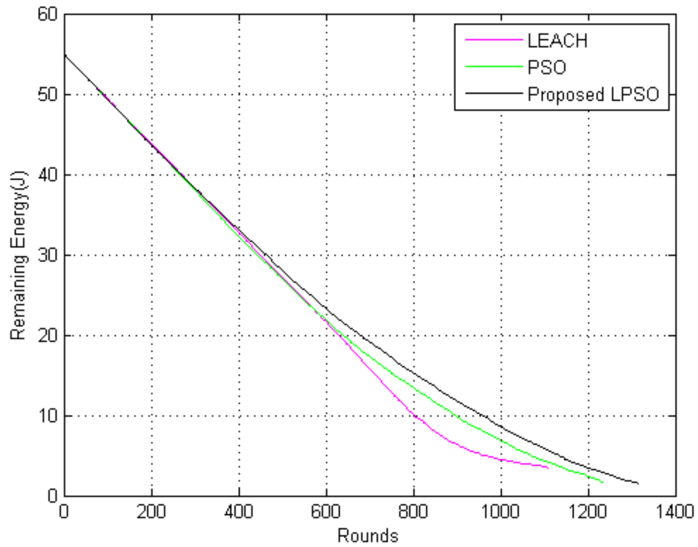

Figure4. Energy is preserved longer period in proposed Algorithm

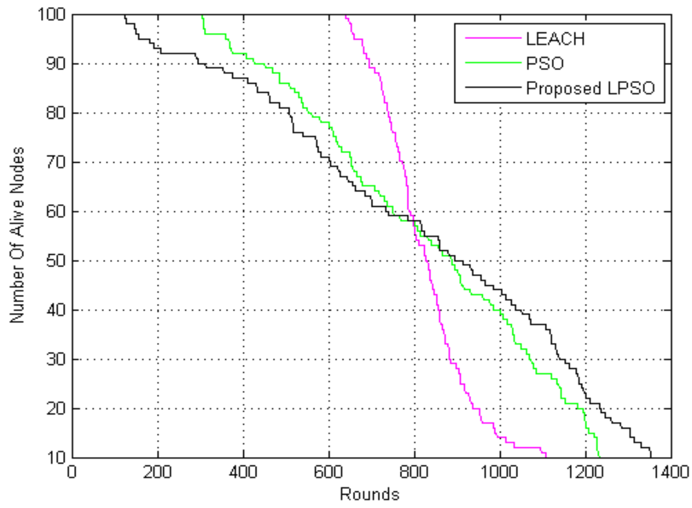

Figure5. Increase in network lifetime using proposed LPSO

5 CONCLUSION AND FUTURE WORK

In this work, we used a two-phase PSO algorithm to optimize the clustering problem in wireless sensor network. In the first phase, the nodes are clustered using factors distance between each CH and its members and distance between CH's distance from sink. In the second phase primary CHs and their members are evaluated in terms of link quality, residual energy and transmission power. Simulation showed that the proposed technique improved over LEACH and PSO-C in both energy saving and network lifetime.

In simulation, performance and functionality are completely affected by mobility of nodes. The extension of this work would be a further discussion of improving functionality and performance of the proposed LPSO by the factor known as mobility.

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