Weighted Clustering using Comprehensive Learning Particle Swarm Optimization for Mobile Ad Hoc Networks

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Abstract

A mobile Ad-hoc network consists of dynamic nodes that can move freely. These nodes communicate with each other without a base station. In this paper, we propose a Comprehensive Learning Particle Swarm Optimization (CLPSO) based clustering algorithm for mobile ad hoc networks. It has the ability to find the optimal or near-optimal number of clusters to efficiently manage the resources of the network. The cluster-heads do the job of routing network packets within the cluster or to the nodes of other clusters. The proposed CLPSO based clustering algorithm takes into consideration the transmission power, ideal degree, mobility of the nodes and battery power consumption of the mobile nodes. It is a weighted clustering algorithm that assigns a weight to each of these parameters of the network. Each particle of the swarm contains information about the cluster-heads and the members of each cluster. It uses the evolutionary capability to optimize the number of clusters. We compare the simulation results with two other well-known clustering algorithms. The results show that the proposed technique is effective and works better than the other two approaches.

Keywords: *Clustering, cluster-heads, ad hoc networks, comprehensive learning particle swarm optimization, routing.*

1. Introduction

A wireless mobile ad hoc network (MANET) is a self-organizing network in which no centralized control exists. It consists of dynamic nodes that can freely move with different speeds and communicate with each other using wireless links. The nodes have limited ability to collect and process information in terms of power consumption and processing speed. Due to the size and battery power limitations, these devices typically have limited storage capacity, energy power and bandwidth. These features of MANETs with non-existence of central base station bring many new problems and challenges.

There are different applications of MANETs such as in military, crisis management, weather forecasting etc. In a cluster-based environment, there are some nodes in the network called cluster-heads which have high processing speed and battery power than the other nodes. Theses cluster-heads are responsible for cluster management and maintenance of the network. A cluster-head allocates the resources to all the nodes that belong to its cluster. In addition to controlling and managing its own cluster, it also communicates with other clusters. It maintains the information about every node within its cluster. Therefore, choosing the appropriate number of cluster-heads that can use the network resources efficiently and adapt to the changing network conditions in MANETs is a challenging task. Choosing optimal number of cluster-heads is an NP-complete problem.

Clustering is a method of organizing things into meaningful groups with respect to their similarities. Elements in a group are similar to each other but are different from other groups. The objective of clustering is to identify the groups in such a way that the identified groups are exclusive so that any instance belongs to a single group. It is very similar to a graph partitioning problem. Optimally portioning a graph is an NP-hard problem with respect to certain parameters.

First, we find the cluster-head and then neighbors of the cluster-head. The neighborhood of a cluster-head is the set of nodes that lie within its transmission range. The set S is called a dominating set in which every vertex of the graph belongs to S or has a neighbor in S. The set of cluster-heads is called the dominating set of the graph. Due to mobility of the network, the nodes can go outside the transmission range of their cluster-head and move into another cluster thus changing their neighborhood. This can change the number of clusters and number of nodes in a cluster but this does not result in a change of the dominant set at all. Clustering of nodes in MANETs is one of the biggest challenges. Finding the optimal number of clusters that cover the entire network becomes essential and an active area of research. Although, several authors have proposed different techniques to find the optimal number of clusters, none of them addresses all the parameters of a mobile ad hoc network. Clustering has several advantages in MANETs. The system performance can be improved by allowing the reuse of resources due to clustering because each group of nodes can communicate with each other without affecting the other groups. Secondly, it optimally manages the network topology by dividing the task among specified nodes called cluster-heads, which is very useful for network management and routing [3].

There are some requirements of clustering in MANETs. The clustering algorithm must be distributed, since every node in the network has only local knowledge and communicates outside its group only through its cluster-head as in case of cluster-based routing. The algorithm should be robust as the network size increases or decreases; it should be able to adapt to all the changes. The clusters should be reasonably efficient i.e. the selected cluster-heads should cover a large number of nodes as much as possible.

In this work, we propose a Comprehensive Learning Particle Swarm Optimization (CLPSO) based clustering algorithm to find the optimal number of clusters for mobile ad hoc networks. Particle swarm optimization is a stochastic search technique. It has simple parameters that need to be tuned during the execution of the algorithm. It has been an efficient and effective technique to solve complex optimization problems. Each particle contains the IDs of all mobile nodes of the network. The algorithm takes a set of parameters of MANETs into consideration such as mobility of nodes, transmission power, battery power and moving speed of the nodes. It is a weighted clustering algorithm in which each of these parameters is assigned a weight such that the sum of all the weights is equal to one.

The rest of the paper is organized as follows: Section II gives an overview of the existing clustering algorithms for mobile ad hoc networks. Section III describes the algorithm of comprehensive learning particle swarm optimization. Section IV describes our proposed CLPSO based clustering algorithm. Section V shows the experimental results by comparing the proposed algorithm with two other clustering algorithms for ad hoc networks. Finally, section VI concludes the paper.

2. Related work

Gerla et al. proposed the highest connectivity clustering algorithm [5]. It is based on the degree of nodes, which is the number of neighbors of a given node. In the election procedure, each node broadcasts its identifier. Each node computes its degree and the node having the maximum degree becomes the cluster-head. Baker et al. proposed the lowest-ID, known as identifier-based clustering algorithm [6]. It assigns a unique ID to each node and chooses the node with the lowest ID as a cluster-head. It means that whenever a new node with a lowest ID appears, it will become the cluster-head. Chatterjee et al. [3] proposed the Weighted Clustering Algorithm (WCA). It elects cluster-heads according to their weights. It is computed by combining a set of parameters such as battery power, mobility and transmission range. This was the first weighted clustering algorithm proposed for MANETs.

Turgut et al. proposed a genetic algorithm based clustering algorithm [4]. In their approach, the genetic algorithm is used to optimize the number of clusters in an ad hoc network. It is also a weight-based algorithm. Another clustering algorithm based on d-hops has been proposed in [7].

The basic problem with all these heuristic-based algorithms is that none of them include all the basic parameters of MANETs. WCA was the first algorithm that includes maximum number of parameters but it does not find optimal number of clusters in the network. The approach of the genetic algorithm was used to address the problem of optimality. When we compare GA with PSO, GA is found to be more computationally intensive than PSO because it performs crossover and mutation in each generation which requires extra processing at each node, whereas, PSO has a simple velocity update equation. Since wireless nodes have limited battery and processing capabilities, PSO is more suitable than genetic algorithm for finding optimal number of clusters in an ad hoc network.

3. Comprehensive learning particle swarm optimization

Particle swarm optimization (PSO) is a stochastic optimization technique developed by Eberhart and Kennedy in 1995, inspired by the social behavior of bird flocking or fish schooling. In PSO, each single solution is a "bird" in the search space which we call as a "particle". A fitness value is associated with each particle which is evaluated by the fitness function to be optimized, and has velocity which directs the flying of the particle [1]. Unlike other evolutionary computation algorithms, a velocity is associated with each particle. Particles fly through the search space and adjust their velocities dynamically according to their historical behaviors. This phenomenon leads the particles to fly towards the better and better search area in the search space [8-11].

It is computationally inexpensive, requires only primitive mathematical operators in terms of both memory requirements and speed. This feature suggests that PSO is a potential algorithm to optimize clustering in a mobile ad hoc network because these kinds of networks have limited resources. Particle positions and velocities are generated randomly in the beginning. The algorithm then proceeds iteratively and updates all velocities and positions of all the particles as follows:

$$v_i^d = w\, v_i^d + c_1\, r_1\, (p_i^d - x_i^d) + c_2\, r_2\, (p_g^d - x_i^d) \quad (1)$$

$$x_i^d = x_i^d + v_i^d \quad (2)$$

where:

- $d = 1,2,\ldots,D$ is the number of dimensions
- $i = 1,2,\ldots,N$ is the size of the population
- w is the inertia weight
- c_1 and c_2 are two positive constants

- r_1 and r_2 are two random values in the range [0,1]

The equation (1) calculates the new velocity of the i^{th} particle by taking into consideration three terms:

- The particle's previous velocity
- The distance between the particle's previous best position and current position
- The distance between the best particle of the swarm

The equation (2) is used to calculate the new position of a particle. The inertia weight is used to control the impact of the previous history explored by a particle on the current velocity. If we increase the value of inertia weight, it favours exploitation and if we decrease the value of inertia weight, it favors exploration. The basic problem with the original PSO is that it restricts the social learning aspect only to the gbest. If gbest is far away from the global optimum then the particles will go to the gbest region and get trapped in a local optimum. Comprehensive learning particle swarm optimization (CLPSO) has the potential to move the particles in larger search space to fly. The information in the swarm will be used more effectively to generate better solutions in CLPSO. In CLPSO, pbest position of a particle is updated by using pbest positions of all the particles in a swarm. This strategy ensures the diversity of the swarm and discourages the swarm to go into premature convergence.

The comprehensive learning PSO uses the following equation for updating velocity of a particle:

$$Vi^d = w * v_i^d + c * rand_i^d * (pbest^d_{fi(d)} - x_i^d) \qquad (3)$$

where,

- $f_i = [f_i(1),f_i(2),\ldots,f_i(d)]$ describes which particles' pbests the particle i will use
- $pbest_{fi(d)}$ is the dimension of any particle's pbest including its own pbest

The algorithm employs a tournament selection procedure for updating the particle's dimension. First, it selects two particles randomly from the population excluding the particle whose velocity is updated. Then it compares the fitness values of these two particles' pbests and selecting the dimension of the better one to update its velocity.

The main difference between CLPSO and the original PSO is that instead of using particle's own pbest and gbest, all particles' pbest can be used to guide the particle's flying direction. This strategy increases the diversity of a swarm when solving complex multi-dimensional problems. In this strategy, the particles can fly in other directions by learning from other particles' pbest. Therefore, this strategy has the ability to jump out of the local optimum by using the cooperative behavior of the whole swarm [1].

4. Proposed technique

In the proposed approach, the CLPSO is used for finding the optimum number of clusters in a mobile ad hoc network for efficient routing. It is a weighted clustering algorithm that selects the cluster-heads based on the weight of each node i.e., W_v of each node v [2]. W_v is defined as:

$$W_v = w_1D_v + w_2S_v + w_3M_v + w_4P_v \qquad (4)$$

where:

- D_v is the degree difference
- S_v is the sum of distances of the members of the cluster-head
- M_v is the average speed of the nodes

- P_v is the accumulative time of a node being a cluster-head

The sum of weights is $\sum w_i=1$ and the node v with the minimum W_v is chosen as the cluster-head. Once a node becomes the cluster-head, neither that node nor its members can participate in the cluster-election procedure further. The cluster-head election algorithm will terminate once all the nodes either become cluster-heads or members of a cluster-head. Each node in the search space has a unique ID and each particle contains the IDs of all the nodes of the network. These unique IDs are used to encode the particles. The proposed algorithm is given in Figure 1.

1. Initialize the population of particles randomly, and initialize the general parameters of CLPSO algorithm.
2. Calculate the fitness value of each particle. The individuals are sorted according to the value of the objective function, which is the sum of all W_v values of cluster-heads in a particle.
3. Select particle neighbors for updating its velocity.
4. Update the position of gbests and pbests as:
   If Fitness (X_i) > Fitness (pbesti) then pbesti = X_i and
   If Fitness (X_i) > Fitness (gbesti) then gbesti = X_i.
5. Update velocity and position of each particle according to equations (1) and (2)
6. Check the stopping criteria.
7. Report the global best particle as the solution of the problem

Figure 1. The Proposed Algorithm

The algorithm iteratively goes through each node in the particle and checks three conditions to decide whether a node can become a cluster-head or not. The conditions are:

- If it is not already a cluster-head.
- If it is not a member of any cluster.
- Number of neighbors of a node is less than the predefined maximum allowed number of neighbors of a node.

If a node fulfils the above three conditions, it is chosen as a cluster-head. After the cluster-heads are chosen, the already calculated value of W_v of each node is used to find out the fitness of each particle by taking the summation of all W_v values of all cluster-heads in this particle. This process continues until the maximum number of iterations is reached. When the algorithm converges, the global best particle is reported as the final solution.

5. Experimental results

We implement the proposed algorithm in Matlab 7.0. We conduct the experiments in a machine with 1.75GHZ dual processors with 1GB of RAM. We perform experiments of M different nodes on a 100 x 100 and 500 x 500 grids. All the nodes can move in all possible directions with displacement varying uniformly between 0 to maximum value (max_disp). The transmission power of each node is set to 30. In our experiments, M is varied between 20 and 80. The maximum number of nodes that a cluster can handle is 10. This restriction will ensure uniform distribution of nodes in each cluster and efficient medium access control (MAC) functioning for an ad hoc network.

The parameters of CLPSO are initialized as follows:

- The population size is set to the number of nodes
- The maximum generations are set to 1000
- The inertia weight w is set to 0.694
- The learning factors c_1 and c_2 are set to 2

We compare the results of the proposed approach with two other well-known algorithms for mobile ad hoc networks clustering i.e., Weighted Clustering Algorithm (WCA) [3] and Divided Range Particle Swarm Optimization (DRPSO) based clustering [2]. The same values of all different parameters are used for the three algorithms. The results are obtained after performing fifty simulations of each algorithm and then taking their averages. The simulations are performed by varying the number of nodes in the network and the transmission range of the mobile nodes.

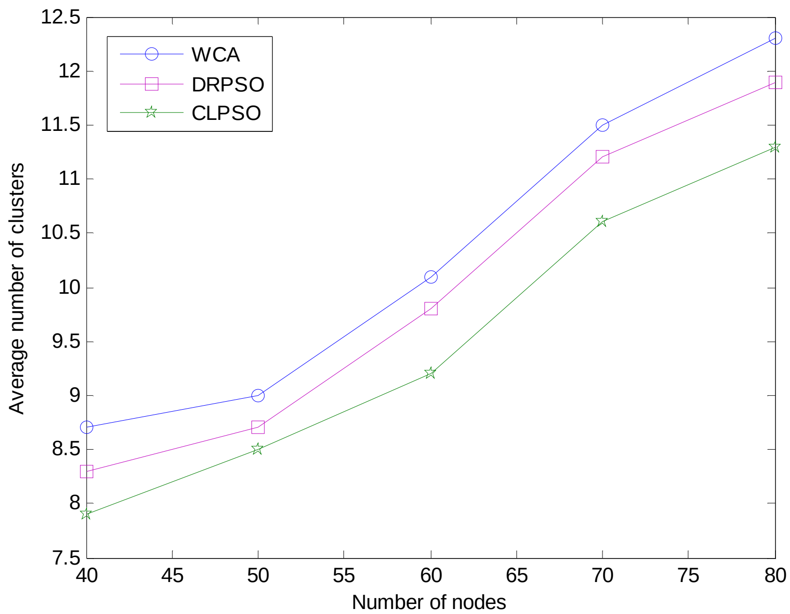

Figure 2. Average number of clusters for WCA, DRPSO and CLPSO in 100x100 m^2 area with transmission range equal to 35.

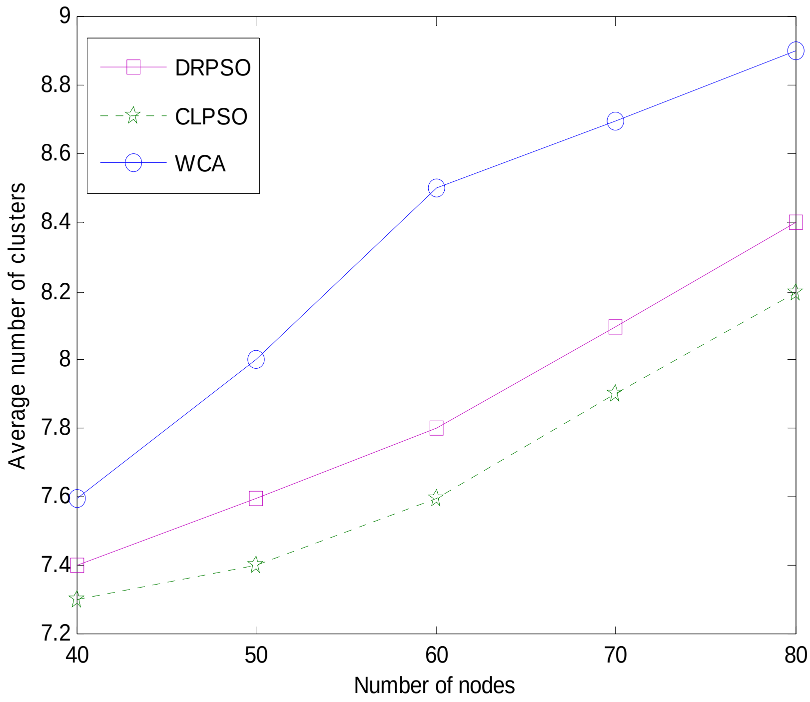

Figure 3. Average number of clusters for WCA, DRPSO and CLPSO in 500x500 m^2 area with transmission range equal to 35.

As can be seen in Figure 2, our proposed algorithm based on CLPSO finds less number of clusters to cover the whole network than WCA and DRPSO in the same environment i.e., 100 x 100 m^2 area with a transmission range of 35.

Figure 3 shows the experimental results performed on a 500 x 500 m^2 area with a transmission range of 35. The average numbers of clusters are less in case of CLPSO as compared to WCA and DRPSO. We also evaluate the performance of the three algorithms by keeping the nodes constant and increasing the transmission ranges of the mobile nodes for both 100 x 100 m^2 and 500 x 500 m^2 areas. Figure 4 and 5 show that the proposed algorithm works better than the other two algorithms in terms of producing the average number of clusters. This shows the robustness of the algorithm in terms of parameters setting.

The results show that the proposed approach covers the whole network with minimum number of clusters that can reduce the routing cost of the network. This will help to minimize the number of hops and the delays of packets transferred in a cluster-based routing environment. The numbers of clusters are large when the transmission ranges of nodes are small. From the results, it is very clear that the proposed algorithm performs better than other two algorithms in a mobile ad hoc network environment.

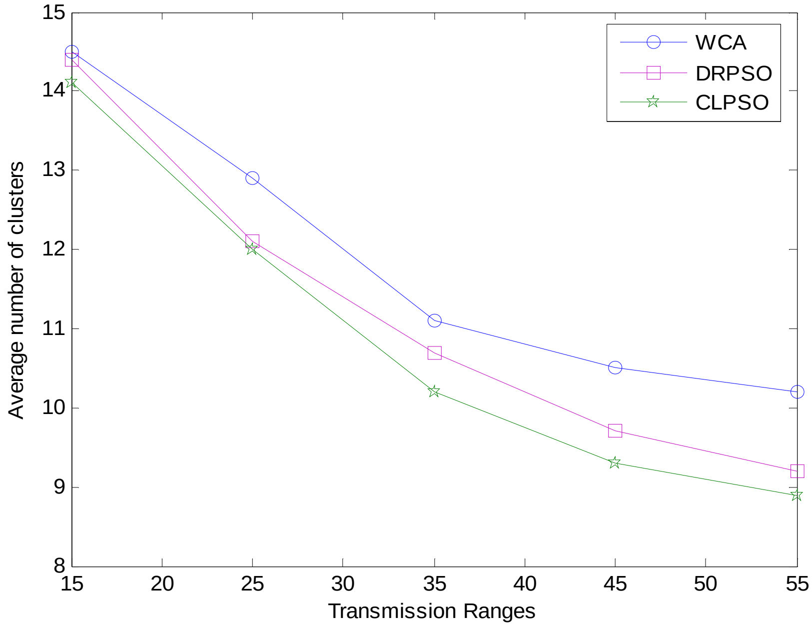

Figure 4. Average number of clusters for WCA, DRPSO and CLPSO for 80 nodes on a
100 x 100 m^2 area.

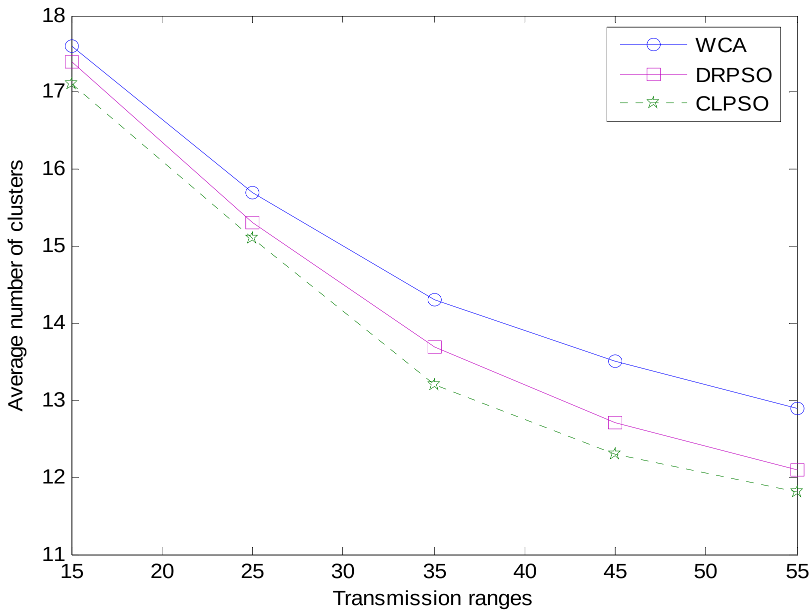

Figure 5. Average number of clusters for WCA, DRPSO and CLPSO for 80 nodes on a 500 x 500 m^2 area.

6. Conclusion

In this paper, we have proposed a weighted clustering algorithm using Comprehensive Learning Particle Swarm Optimization (CLPSO) for mobile ad hoc networks. The algorithm attempts to minimize the average number of clusters by using its evolutionary capabilities so that the routing can be performed in an efficient manner. By using minimum number of nodes to forward the packets, the routing delay can be significantly reduced. It uses a set of parameters for the election of a cluster-head hence that node is elected as the cluster-head which is more powerful than the other nodes. It also has a check on the maximum number of nodes that a cluster can handle which leads to the efficient usage of the medium access control (MAC) sub-layer. The simulation results show that it is an effective and robust technique for clustering in a mobile ad hoc network environment. The results of the proposed technique are also compared with two other well-known clustering algorithms. The results exhibit the promising capability of the proposed technique and clearly show that it works better than the other two clustering techniques

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