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Quality Of Service Based Secure Clustering For Mobile Adhoc Networks Using Particle Swarm Optimization Based Clustering Algorithm

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ABSTRACT

A mobile ad hoc network (MANET) is dynamic natured wirelessly connected nodes and has no fixed infrastructure. Efficiency of energy is one of the main requirements of a MANET. Clustering in MANETs can provide an energy-efficient solution. Clustering involves selection of cluster-heads (CHs) for each cluster and fewer CHs means greater energy efficiency. In this work a multi-objective particle swarm optimization (MOPSO) algorithm is proposed to optimize the number of clusters in an ad hoc network. The proposed algorithm takes into consideration the nodes QoS parameters: packet drop rate, battery power of node and available bandwidth. The main advantage of this method is that it provides multiple solutions at a time. These solutions are achieved through optimal Pareto front. MATLAB and NS2 is used for simulation of the proposed approach. The performance of the proposed approach is explained by varying the number of clusters and transmission range of nodes.

Keywords:*Mobile adhoc networks (MANET), Multi-objective particle swarm optimization(MOPSO), Clustering; Cluster-head (CH)*

1. INTRODUCTION

Mobile ad-hoc network (MANET)

A MANET is a wireless mobile ad-hoc network which is self organizing network without any centralized control. It consists of dynamic nodes that are capable to freely move with different speeds and can communicate with each other using wireless links. These nodes have limited ability to collect and process information due to its power consumption and processing speed. Due to small size and limited battery power, these devices have limited storage capacity, energy power and bandwidth. These limitations of MANETs bring many new problems and challenges. MANET has wide applications in military, crisis management, weather forecasting etc. In cluster-based network, there are some nodes called cluster-heads which have high processing speed and battery power than the other nodes. These CHs manages the cluster and maintains the network. The CH allocates the resources to all the nodes within its cluster. It can also communicate with other clusters. It stores the information about all the nodes within its cluster. The challenging task of a MANET is to choose the appropriate number of CHs and to adapt to the changing network conditions. Choosing of optimal number of CHs is an NP-complete problem [3].

Clustering in MANET

Clustering is a method of dividing the network into meaningful groups with respect to certain similarities. Elements within a group have similarities but they differ in other groups. Partitioning a network is similar to a graph partitioning problem. First, we find the cluster-head and then its neighbours. The neighbourhood of a cluster-head is the setof all nodes that are within its transmission range. The set of

cluster-heads is called the dominating set of the graph. Due to mobility of the nodes and network, the nodes may go outside the transmission range of their cluster-head and get into another cluster. This may change the number of clusters and number of nodes in a cluster but this will not make a change in the dominant set. Clustering of nodes and finding the optimal number of clusters in the entire network becomes very essential. Several authors have proposed different techniques to find the optimal number of clusters, none of them addresses all the parameters of a MANET. Clustering has several advantages in MANETs. Through clustering each group of nodes can communicate with each other without affecting other groups. Secondly, it manages the network topology by dividing the task among cluster-heads. There are some requirements of clustering in MANETs. The clustering algorithm must be distributed, since each node in the network has only knowledge within its group and communication to outside its group is only possible through its cluster-head as in case of cluster-based routing. The algorithm should be robust to adapt to all the changes in the network. The clusters should be reasonably efficient to cover a large number of nodes as much as possible.

PSO

Particle swarm optimization (PSO) is population based stochastic optimization technique [12], in which each particle in the initial population represents individual solution. A swarm represents group of solutions. The algorithm uses fitness function to evaluate optimal solution from group of solutions. It maintains two values *gbest* and *lbest*. g*best* represent global best solution obtained in the generation and *lbest* of each particle represent the local best solution obtained by the particle. These values are updated in each generation by comparing the old *gbest* and old *lbest* values with new *gbest* and new *lbest* values. The velocity and position of each particle is updated based on Eq. (1) and Eq. (2). The algorithm repeat the process until the maximum number of generation is reached or the best fitness is obtained.

$$v_i^{k+1} = w_k \times v_i^k + c_1 r_1 (lbest - x_i^k) + c_2 r_2 (gbest - x_i^k) \qquad (1)\&(2)$$
$$x_i^{k+1} = x_i^k + v_i^{k+1}$$

where inertia weight, $w_k = \dfrac{(w_{start} - w_{end})}{(1+e^{u(k-n\times gen)})} + w_{end}$ (3)

and $u = 10^{(\log(gen)-2)}$

The inertia weight *w* controls the momentum of particle based on previous velocity. In this paper we applied sigmoid increasing inertia weight (SIIW). SIIW is computed based on Eq. (3), where *k* represent the generation, w_{start} and w_{end} represent the inertia weigth at start and end of each iteration respectively. g*en* specifies maximum number of generations allowed. *c1* and *c2* are constants in the range (0,4). *r1* and *r2* are random numbers in the range (0,1). The PSO process covers both local optima and global optima as w_k varies from small inertia weight at beginning to large inertia weight at end. Usually the constants are selected as 2. The values of *c1* and *c2* can be equal and (*c1* + *c2*) <= 4.

Compared to GA, PSO is easy to implement, and it does not use crossover and mutation operation. The new population is generated by updating the velocity and position of each particle. PSO requires memory to store the *gbest* and *lbest* values. Only the selected best particle shares the *gbest* value to others. PSO is computationally more efficient as compared to GA.

The rest of this paper is organized as follows: Section 2 gives an overview of the previous PSO based clustering algorithms for MANET. Section 3 describes multi objective optimization. Section 4 includes project description with proposed MOPSO based clustering algorithm. Section 5 deals with experimental results. The section 6 concludes the work.

2. RELATED WORK

Hamid Ali, Waseem Shahzad, F.A.Khan propose a multi-objective solution by using multi-objective particle swarm optimization (MOPSO) algorithm.The algorithm optimizes the number of clusters in an ad hoc network as well as energy dissipation in nodes in order to provide an energy-efficient solution and reduce the network traffic.The proposed algorithm takes into consideration the degree of nodes, transmission power, and battery power consumption of the mobile nodes [1].

J.J.Liang, A.K.Qin presented a variant of particle swarm optimizers (PSOs) that they call the comprehensive learning particle swarm optimizer (CLPSO), which uses a novel learning strategy whereby all other particles' historical best information is used to update a particle's velocity [2].

Waseem Shahzad, Farrukh Aslam Khan, and Abdul Basit Siddiqui proposed a comprehensive learning particle swarm optimization based clustering algorithm for mobile Ad-hoc network. The algorithm proposed here has the ability to find the optimal or near-optimal number of clusters to efficiently manage the resources of the network. The 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 [4].

Margarita Reyes-Sierra and C.A. Coello Coello proposed a MOPSO based clustering algorithm approach. The success of the Particle Swarm Optimization (PSO) algorithm as a single-objective optimizer (mainly when dealing with continuous search spaces) has motivated researchers to extend the use of this bio-inspired technique to other areas. One of them is multi-objective optimization [14].

K.E.Parsopoulos and M.N.Vrahatis presented a paper which constitutes a first study of the PSO method in multi-objective optimization (MO) problems. The ability of PSO to detect Pareto Optimal points and capture the shape of the Pareto Front is studied through experiments on well-known non-trivial test functions [15].

R.T. Marler and J.S. Arora performed a survey of current continuous nonlinear multi objective optimization (MOO) concepts and methods [16]. It consolidates and relates seemingly different terminology and methods.

C. A. Coello Coello proposed an approach in which Pareto dominance is incorporated into particle swarm optimization (PSO) in order to allow this heuristic to handle problems with several objective functions. Unlike other current proposals to extend PSO to solve multi objective optimization problems, their algorithm uses a secondary (i.e., external) repository of particles that is later used by other particles to guide their own flight [10].

3. MULTI OBJECTIVE OPTIMIZATION

Multi objective optimization problem (MOOP) deals with more than one objective function and results in multiple optimal solutions. MOOP involves two main goals: 1. Find set of solutions which lie on pareto optimal front and 2. Find set of solutions which cover the entire range of pareto optimal front. The main task of MOOP is to find set of pareto optimal solution. Non dominated solutions obtained are said to be pareto optimal solutions. Multiple solutions obtained are classified as non dominated solutions and dominated solutions. Solution *A* dominates solution *B*, if *A* is no worse than *B* and *A* is strictly better than *B* in at least one objective. *A* and *B* are non-dominated, if both are not worse or not better than each other.

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Pareto optimal front is the curve obtained by joining all pareto optimal solutions. Pareto optimal set is the set of all pareto optimal solutions. In the proposed work, the fitness is evaluated based on three objective functions *F1*, *F2* and *F3*. *F1* measures the trustworthiness of the node. *F2* and *F3* measures the QoS parameters: battery energy and bandwidth available at the node.

4. PROJECT DESCRIPTION

PSO can handle both continuous as well as discrete variable problems. The implementation of PSO is very easy and few lines of code are required for implementation. It is also computationally inexpensive in terms of memory as well as speed and is suitable for multi-objective optimization. These features suggest that PSOis a potential algorithm for optimizing clustering in a mobile ad hocnetwork. In this work, a multi-objective particle swarm optimizationalgorithm is used to solve the problem of clustering in a mobilead hoc network. Each particle in MOPSO represents coordinatesof N number of cluster-heads.

Proposed work

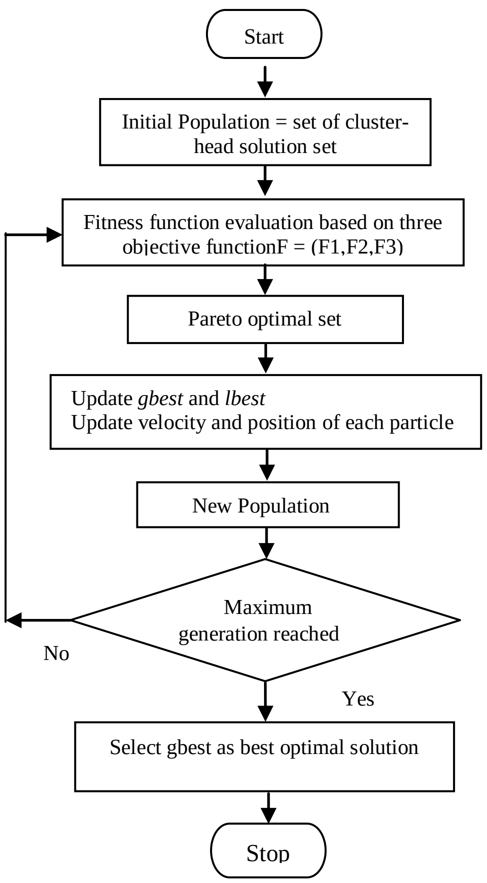

Fig.1 Flowchart of the proposed algorithm.

The Fig.1 is the flowchart explaining the working of proposed MOPSO algorithm.

Initial population

The process start with set of randomly selected cluster solution sets. Each solution includes set of *ID* of the nodes, elected as CH. The steps involved in initial population generation are as follows.

1. Generate the initial population of the algorithm that includes set of randomly selected CH solution set ().

1.a. Let N= { set of nodes in network } and $\hat{CH}_i = \phi$

1.b. Randomly select a node *k* as CH.

$\hat{CH}_i = \hat{CH}_i \cup k$

1.c. $N = N - \{k \cup N(k)\}$ where *N(k)*- one hop neighbour of *k*

1.d. Repeat steps from 1.b. until all network nodes are covered.

2. Repeat steps from 1.a. to generate required number of different CH solution set.

Fitness evaluation

The fitness function *F* for each solution in the population is evaluated based on Eq. ().

Fitness function, $F = (F1, F2, F3)$

F1 deals with trust level of nodes, *F2* and *F3* deals with QoS parameters: battery energy and bandwidth available on nodes.

F1- Trust value of node

The objective function *F1* describe the trust value of node, computed based on

loss ratio (LR) – number of packets dropped by node
packet delivered (PD) – number of packets delivered without alteration
error rate (ER) – number of packets delivered with alteration

$$F1 = \min_{j \in \hat{CH}} (TV_{CH_j})$$

where *TV = F(LR,PD,ER)*
We considered the following linguistic variables:
Packet drop rate LR = {low, medium, high}
Packet forwarded successfully PD = {not successful,partially successful, successful}
Packet forwarded with alteration ER = {altered,unaltered}
Trust level = {not trusted, low, average, normal, fullytrusted}

Fig.2 shows the structure of fuzzy controller. This model describes the design of a Fuzzy Logic Controller used to calculate trust value of each node. The controller takes three inputs LR, PD, ER. Fuzzification is carried out using Gaussian member function. A set of 15 rules is used as a rule base for

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trust computation.Some of the Linguistic rules of fuzzy controller are as follows.

If (LR is medium) and (PD is not_successful) and (ER is unaltered) then (TV is not _trusted) (1)
If (LR is high) and (PD is successful) and (ER is unaltered) then (TV is low) (1)
If (LR is low) and (PD is partially_successful) and (ER is altered) then (TV is average) (1)
If (LR is medium) and (PD is partially_successful) and (ER is unaltered) then (TV is normal) (1)
If (LR is low) and (PD is successful) and (ER is unaltered) then (TV is fully _trusted) (1)

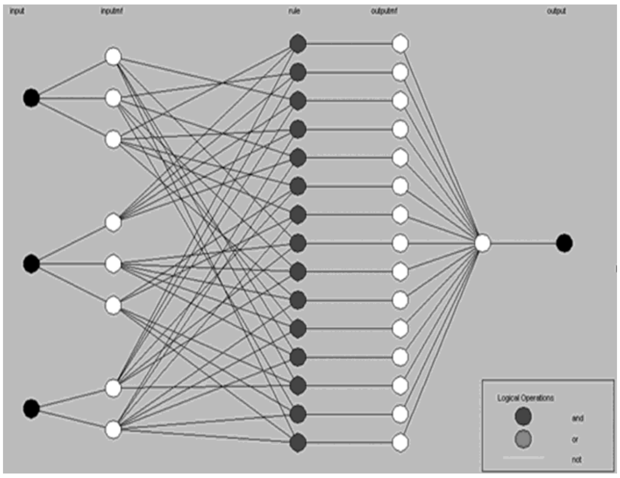

Fig.2. Structure of fuzzy controller.

F2- Remaining lifetime of node

The objective function *F2* describe the remaining lifetime of node, computed based on energy drain rate and residual energy of node.

$$F2 = \min_{j \in \hat{CH}} \left(\frac{E_{CHj}}{DR_{CHj}} \right)$$

where $DR_{CHj} = \alpha \times DR_{oldCHj} + (1 - \alpha) \times DR_{newCHj}$

F3- Available bandwidth of node

The objective function *F3* is computed based on available bandwidth of node and number of nodes in current CH solution set.

$$F3 = \frac{\min_{j \in \hat{CH}} (BW_{CHj})}{n}$$

where *n* is number of cluster points in $\hat{CH}$

Generation of next population

Set of pareto optimal solutions are selected for next population. The solutions that are non-dominating with each other are said to be pareto optimal solutions. Solutions *s1* and *s2* are non-dominating if they are not inferior with respect to each other. MATLAB function *prtp()* is used to find pareto optimal solution set. *gbest* and *lbest* values are updated and buffered, by comparing with the old values. The steps involved in updating *gbest* and *lbest* values are as follows.

1. For each

   1.a. update *lbest* = best(old *lbest*, current solution)

   End for

2. Update *gbest* = best(old *gbest*, current solution)

5. EXPERIMENTAL RESULTS

Fitness function of each population is evaluated by means of simulation using MATLAB and NS2. The fuzzy controller to evaluate the trust value is based on sugeno fuzzy model. The defuzzification method used is wtaver. The fuzzy model is trained with the data set of size 65×4. The fuzzy system is trained for 10 epochs. Fig.3. shows the rule viewer of the fuzzy system for the input LR=1.39, PD=8.49, ER=2.11. The trust value computed is 8.06. The network is simulated with 60 nodes within the simulation area of 1000×1000m. The mobility of the node is based on random waypoint mobility model. The experiment is conducted by varying the speed of the mobile nodes as 10, 15, 20, 25, 30 m/s. The transmission range of each node was varied as 10, 20, 30, 40 m. The number of nodes was varied between 10 and 60.

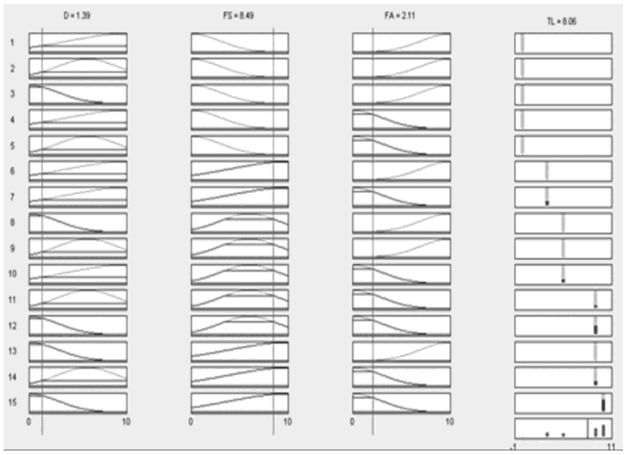

Fig.3. Rule viewer of the fuzzy system for the input LR=1.39, PD=8.49, ER=2.11.

Fig.4. shows the variation of the number of cluster-heads with respect to the transmission range. The result shows that the average number of cluster-heads decreases with increase in the transmission range. Compared to CLPSO and WCA the proposed approach shows maximum transmission range with less no: of clusters.

Fig.5. shows the variation of energy consumed with respect to the transmission range. The result shows that the energy consumed decreases with increase in the transmission

range. Compared to CLPSO and WCA the proposed approach shows less energy consumption with maximum transmission range. Currently we are working in evaluating theperformance of the proposed algorithm based on factors such as packet drop rate, transmission overhead and to compare the performance of the proposed approach with the clustering algorithms WCA and CLPSO.

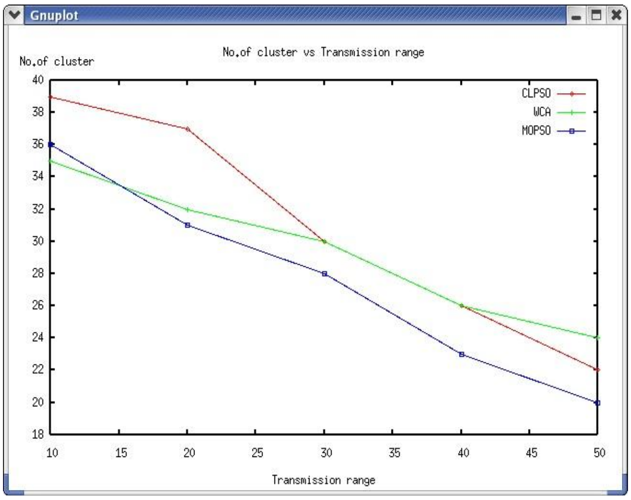

Fig.4. Number of clusters Vs Transmission range.

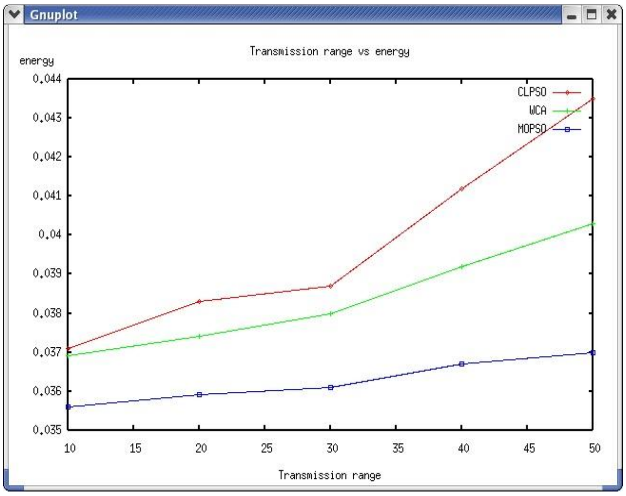

Fig.5. Energy consumed Vs Transmission range.

6. CONCLUSION

The project is summarized as follows. This work presents a multi-objective particle swarm optimization algorithm for clustering in mobile ad hoc networks (MANETs). The proposed approach has the ability to find out multiple optimal solutions. By minimizing the number of clusters we can reduce the routing cost of a packet. It also makes the routing energy-efficient because less number of nodes are involved for routing a packet. The evolutionary capability of the algorithm allows it to search large search space. The performances of the proposed approach are compared with the existing algorithms such as WCA and CLPSO and finally concluded that the proposed algorithm shows better performance.

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