REVIEW OF RESEARCH
IMPACT FACTOR : 5.2331(UIF) UGC APPROVED JOURNAL NO. 48514 ISSN: 2249-894X
VOLUME - 7 | ISSUE - 10 | JULY - 2018

ENHANCING DATA EFFICIENCY AND LOAD BALANCING TECHNIQUE FOR CLUSTER-BASED MANETS USING ADVANCE DYNAMIC GENETIC ALGORITHMS

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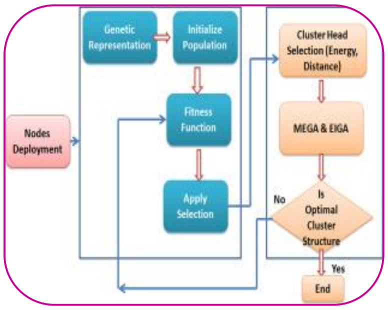
ABSTRACT



Mobile Ad hoc Networks (MANETs) is a kind of self-configuring networks. MANET can also be partitioned into clusters for maintaining the network structure. Generally, clustering is used to reduce the size of the topology and to accumulate the topology information. MANET has characteristics of topology dynamics due to factors such as energy conservation and node movement that leads to dynamic load-balanced clustering problem (DLBCP). Load balancing and reliable data transfer between all the nodes are essential to prolong the lifetime of the network. It is necessary to have an effective clustering algorithm for adapting the topology change. In this, we used energy metric in Genetic Algorithm (GA) to solve the DLBCP. It is important to select the energy-efficient cluster head for maintaining the cluster structure and balance the load actively. In this work, we used advanced dynamic genetic algorithms such as Memory Enhanced Genetic Algorithm (MEGA) and Elitism based Immigrants Genetic algorithm (EIGA) and to solve DLBCP. These schemes, select an optimal cluster head by considering the distance and energy parameters. We used EIGA to maintain the diversity level of the population and MEGA to store the old environments into the memory. It promises the energy efficiency of the entire cluster structure to increase the lifetime of the network. Experimental results show that the proposed schemes increase the network lifetime and reduces the total energy consumption. The simulation results show that MEGA gives a better performance than EIGA in terms of load-balancing.

KEY WORDS : *network structure , Genetic Algorithm (GA) , Memory Enhanced Genetic Algorithm (MEGA).*

INTRODUCTION

The network topology of MANETs [1] changes erratically and dynamically because the connection between the nodes may vary with time due to existing node departures and new node arrivals. In a MANET, breaking of communication link is very frequent, as nodes are free to move anywhere [2]. Dynamic optimization problem [24] caused by static routing path in MANET. One of the most critical issues in MANET is the significant deference's in term of energy capacity between the nodes inducing a load imbalance. Thus, sharing the load between the overloaded and idle nodes is a necessity in MANET. Due to node mobility and dynamic topology changes, load-balancing is more challenge going in MANET[6]. So, MANET needs client cluster structure to make load-balancing, energy-efficiency and topology control. It is difficult to know the number of cluster members that can be served by each potential cluster head. Dynamic Genetic Algorithms (DGAs) play an important role to solve the dynamic load clustering problem in MANET. It also finds optimum clusters that cover the minimum set of nodes in a MANET. Biradar and Thool [4] used a genetic algorithm in routing during route discovery to get an optimum solution for route maintenance. It deals with all the unfeasible chromosomes using optimization technique[7]. We developed a DGA for finding the optimal set of clusters with cluster heads for solving dynamic optimization problem. However, previous works not focus greater consideration to the dynamism of topology. Several methods are proposed for clustering using Genetic algorithms(GA) in MANET such as Genetic Algorithm Simulated Annealing[5], GA for Cluster Leader Election [8] and Elitism-based immigrants schemes[9]. These schemes are not adapting to the mobility and causes routing overhead due to exchange of control packets. GA provide a perfect scheme for optimal results in a network topology structure [10], GA provides network optimization for shortest path routing[11], [12], Energy-Efficient QoS Multicast Routing [3],Energy-efficient multi-metric QoS routing[27] and optimum routing [13] to enhance routing performance. However, these schemes don't perform well to the dynamism of topology and load-balancing. Multi-cluster system [31] achieves dynamic load balancing for task and resources assignment. Previous research works only focused on clustering where cluster heads are selected in the network. In this paper, the proposed schemes form the clusters with optimal cluster heads.

Moreover, cluster formation is based on the metrics such as node's energy and distance. The node with high energy and highest degree is selected as cluster head. The proposed schemes used EIGA for adopting the topology change to maintain the diversity level of the population and MEGA stores the old environments into the memory to deal with the DLBCP. The memory scheme aims to improve the performance of GAs for Dynamic Optimization Problems (DOP). It stores recent information from the current environment. Then, the stored information can be reused in new environments to reduce overhead. We presented performance evaluation, which shows that the proposed scheme has finding optimal clusters to maintain the stable network structure. The proposed scheme can significantly improve the packet delivery ratio and low routing overhead. The proposed work summarizes as follows.

- We formulated dynamic load-balanced clustering problem with the existing dynamic optimization problem.
- A genetic operation such as selection, fitness function, mutation and crossover applies for cluster head selection. Distance of nodes, Data transfer and energy parameters are considered to select a cluster head and to balance the load.
- We used Elitism-based Immigrants Genetic Algorithm and Memory Enhanced Genetic Algorithm to solve dynamic changing environment within a cluster.
- The proposed schemes are examined with performance metrics such as data efficiency a packet delivery ratio, routing overhead and total energy consumption of the network.

The remainder of the paper organized five sections. Section 2 summarizes related work. Section 3 presents our proposed methodology for analysis of a Memory Enhanced Genetic scheme and Elitism-based Immigrants Genetic scheme for changing dynamic topology of the network. Section 4 presents our simulation results and a relevant performance analysis. Finally, Sections 5 presents our conclusions and future direction.

2. Related Work

In recent years, studying genetic algorithm for DOP has attracted and growing interest due to its importance in real world applications. The network topology changes rapidly in MANET due to the battery exhaustion and node mobility. Topology dynamics of MANET provides great issues to load-balancing of the node. Clustering schemes achieve scalability and reduce the routing overhead in the network. In order to achieve fairness and uniform energy consumption, an efficient clustering scheme produces a load-balanced cluster head to adapt topology dynamics. Hui Chengaetal.[23] proposed two multi-population GAs such as forking GA and shifting balance GA. Both are enhanced by an immigrants scheme to hold the dynamic optimization problem. It is consumed more energy to handle control messages during network topology changes. Huic Cheng et al.[14] formulated the dynamic load-balanced clustering problem into a dynamic optimization problem. They used the series of dynamic genetic algorithms to represent a feasible clustering structure in MANET. Its fitness is evaluated based on the load-balance metric. It is not focusing on dynamic multi-metric clustering problem.

3. Proposed work

In MANETs, an effective clustering algorithm adapts to topology change and produces the new load-balanced cluster heads. We first formulate the dynamic load-balanced clustering problem into a dynamic optimization problem (DOP). Then, we used a Memory Enhanced Genetic scheme and Elitism-based Immigrants Genetic scheme to solve the DLBCP in MANET. Each individual represents a feasible clustering structure and its fitness is evaluated based on the load-balance metric energy metric and data efficiency. The cluster head is selected by considering the clustering parameters such as energy and distance of nodes. The immigrant-based GA is applied to maintain the diversity level of the population. The memory-based GA is used to store information about the old environments. The dynamic GA schemes obtained efficient cluster structure with cluster head. Dynamic GA for proposed system is presented in Figure 1.

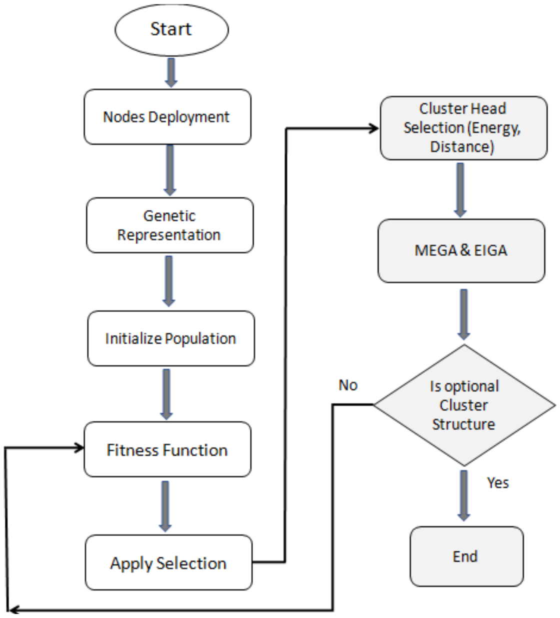


Figure 1: Advance Dynamic GA for proposed system

MANET is represented as a un-directed graph G(Vi; Ej), where Vi represents the set of wireless nodes and Ejrepresents the wireless links connecting two neighboring nodes. Cluster headset over a graph was found by Eq.(1)

$$\{Chead_i \mid i\text{€} \{1,2,3,\ldots n\}, 1>n <30\} \qquad (1)$$

Where $Chead_i$ a cluster headset, n is the number of nodes in graph G(Vi; Ej). Each cluster head set in the network is given by

$$CHeadi= \{c1,c2,\ldots.cj\} \qquad (2)$$

The cluster head degree is a node with highest energy which is denoted as Deg*CE* and the average number of nodes served by each cluster head is denoted as *Avgm* . This scheme aim to reduce the standard deviation of cluster member nodes is given by Eq.(3) and Eq.(4)

$$\sigma Chead_i= \sqrt{\frac{1}{Avgm}\sum_{J=1}^{Avgm}(DCe - dCHi)2} \qquad (3)$$

Then, energy-efficient node of each cluster is found. Energy of each node in a cluster is calculated by Eq.(4)

$$ET = Etx + Erx + Eideal$$

whereEtx and Erx is the energy consumed when the packet is transmitted and received. Then, we selected the minimum standard deviation node with the highest energy node as a cluster head.

3.1. Genetic Representation

Initially, we considered the number of nodes in MANET as population. It is denoted by Eq.(5)

$$P = \{n_1, n_2, n_3, n_4 \ldots. n\mathit{m}\}$$

$\{n1\}$, $\{n2\}$, $\{n_m\}$ are node in a network that represents a gene. Set of permutation nodes of the network is represented as Chromosome that is given by Eq.(6)

$$np_r = n!/(n-r)! \qquad (6)$$

Where n represents the total number of nodes, r represents the elements taken from the given set of n. It guarantees that each chromosome has no duplicate node ID and investigates the dynamism of network topology.

3.2. Population Initialization

In a DGA, each chromosome corresponds to a potential solution. The random immigrant scheme generates anew best child into the population([25]). The initial population Q is composed of nodes having q of chromosomes. Node IDs are generated randomly by permutation to explore the genetic diversity for each chromosome. The initial population is given by Eq.(7)

$$P_{GA} = \{chr_0, chr_1, ..chr_{q-1}\} \qquad (7)$$

3.3. Fitness Function

Fitness function accurately evaluates quality of a given solution. The standard deviation of the cluster head degrees and the energy consumption of cluster head provide a quality solution. It finds the set of cluster heads with highest energy that led the load-balancing problem on the network. For each round, the cluster head is elected by finding the minimum energy consumption node. The load is balanced by selecting nodes with high energy and minimum deviations cluster head. If the current cluster head drawn much energy, another node with high energy is allowed to become the cluster head. The fitness value of chromosome Chri represented as F(Chri).

3.4. Selection

The proposed scheme used a pairwise tournament selection approach [22] to improve the quality of the population because high quality chromosomes alone pass to the next generation. Here, a pairwise tournament selection scheme is implemented without replacement. Tournament size is derived from a random set of chromosomes that keep the selection noise as low as possible. This approach chose a random set of chromosomes that are no overlapping from the population. Then, it selects a best chromosome from each set of chromosomes, which has served as a parent to the next generation. Selection pressure characterizes the selection schemes that are defined as the ratio of the probability of selection of the best chromosome in the population.

$$P_{CH} = \{P_{CH1}, P_{CH2}, ..., P_{CHi}\} \qquad (10)$$

3.5. Memory enhanced GA

MEGA stores the latest information from the current environment to enhance the performance of DOP. It uses redundant representation to store implicitly premium solutions of the current population and in extra memory space explicitly. The stored information is reused in new environments. Old solutions in a new environment will be reactivated in the explicit memory scheme when the current environment changes. The memory scheme is able to achieve the best solution with an old environment. When the environment changes periodically the old environment reappears. A general strategy is to select one memory point to be removed, from which the best individuals are selected from the populations. The following memory replacement strategy procedure is followed for memory point updating.

- Replacing the less important individual with respect to the age, contribution to diversity and fitness, replacing the individual with last contribution to memory variance
- Replacing the most similar individual if the new individual is better
- Replacing the less fit individual of memory points that have the minimum distance between all pairs and having the highest energy node

The memory scheme stores best solutions from the current environment in a memory that can be reused in new environments. The memory is updated in two situations: a change in the environment is detected periodically, and the best individual is stored into the memory from the current environment.

3.5 Procedure for MEGA

```
t:=0, $t_M$:= rand(5,10), ET = 64 joules and di j=30m
randomly initialize population P(0) and memory M(0)
do
evaluate population P(t) and memory M(t)
elite E(t-1) from P(t-1)
replace worst individual with P(t) by the elite E(t-1) from P(t-1)
Elite0(t - 1) = (Elite(t -1)) > ET < di j
If changes fitness
P”(t) := retrieve best individuals from (P(t), M(t))
Else
P0(t) := P(t)
If t = $t_M$ or changes fitness then // time to update memory
If t = $t_M$ then
Bp(t) := retrieve best individual from (P’(t))
If changes fitness then
Bp(t) := E0(t - 1)
If still any random point in memory then
replace a random point with Bp(t)
else
If t = $t_M$ then
retrieve memory point CM(t) closest to Bp(t)
If f (Bp(t)) > f (CM(t)) then
f (CM(t)) := Bp(t)
$T_M$ := t+rand(5,10)
```

```
// Perform genetic operations
P”(t) := select for reproduction (P(t))
Crossover(P00(t); pc) // Generate two offspring chromosomes
Mutate(P00(t); pm) // Generate an offspring chromosome by swapping method
P(t + 1) := P”(t)
End if
Until the termination condition is met (t >tmax)
```

where P(t) and m(t) are the population and memory, respectively, P0(t) is the elite retrieved from p(t) and m(t),Bp(t) is the best individual retrieved from P0(t), CM(t) is the memory point closest to Bp(t).The space taken by the proposed algorithm is O (1) constant space with respect to the input size.It stores only flag of GA (FGA). It is stored in the routing table of the network that can be seen Table 1.

Table 1: Routing table

Ds	routNextHob	routnHopCount	FGA
So#	RREQ.S #	routHop # +1	1

Ds	routNextHob	routHopCount	FGA
So#	RREQ.S #	routHop # +1	0

Ds	routNextHop	routHopCount	FGA
So#	RREQ.S #	routHop # +1	-1

If the value FGA is 1, clustering replaces current generation with elite from the previous generation. If the value ofFGAis 0, clustering uses current generation. The value of FGA-1 indicates that the node has left the network. It means that the network topology was changed.

4. RESULTS AND DISCUSSION

The proposed system has been implemented in network simulator (NS2). The simulation parameter settings are presented in Table 2. 200 nodes were randomly deployed in a 1000 m x 1000 m area of interest. The transmission range of the node was 50 m and initial energy is assigned with 100 joules. Nodes are followed the random way point model[28] that finds the availability of connection paths in MANET. In this simulation, two ray ground propagation model is used because it predicts path loss when the signal received. The proposed scheme analyzed the effectiveness of the two GA schemes such as Elite-based immigrant and Enhanced memory-based immigrant scheme to form stable and optimal cluster structures. The proposed scheme is also evaluated by comparing it with the related DLBCP andGABOC schemes in terms of the packet delivery ratio, energy consumption, throughput and routing overhead. Thesimulation results were studied by varying the network size from 50 to 200. The proposed Energy-Efficient andLoad-Balancing Elite-based immigrant Genetic Algorithm(EELB-EIGA) and Energy-Efficient and Load-Balancing-Memory Enhanced Genetic Algorithm (EELB-MEGA) have been integrated to update the latest information about the environment and provide a optimal solution for load-balancing cluster structure in MANET.

Table 2: Simulation Parameters.

Parameter	Value
Simulation Area	1000 m x 1000 m
Simulation Time	1000 Sec
No of nodes	50
Population size	100
Cross over rate	0.5
Mutation rate	0.005
Number of generations	75
Transmission range	50m
Movement model	Random waypoint
Speed	[10-20] m/s
Packet size	512 bytes
Propagation model	Two ray grounds
Initial energy	100 joules
Transmitting energy	0.8 joules
Receiving energy	0.2 joules

Figure 4 shows the 50 nodes are formed with clusters. Each cluster has nine cluster members and one cluster head. All nodes in the clusters are involved in transmitting their data to the destination through cluster head. Thenode 0 and node 49 is considered as the source and destination, respectively. The proposed schemes considered a random way point model for moving nodes randomly in simulation area. It selects an energy-efficient cluster head by considering the distance and energy of each node in the network. The selected cluster head transmits the data to its neighboring nodes who are considered as its cluster members. Figure 4 shown that the node 7 is selected as the cluster head and it is transmitting the data to its neighbor nodes 0,2,1,3,4,5,6,8,9 who are considered as cluster members ofnode 7. Likewise, other cluster structures are formed. The environment becomes change when the node 7 moves toout of transmission or left from the network. EIGA generates a new population with elite characteristic when theenvironment changes. MEGA scheme provides an old environment for forming a cluster structure when the networkenvironment does not change that reduce complexity.

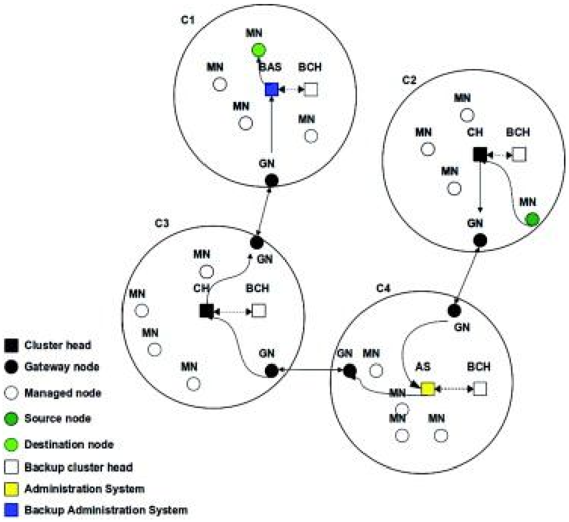


Figure 4: Cluster formation in MANET.

4.1. Total energy consumption

Figure 5 is plotted across the number of nodes and the total energy consumption of various nodes. Figure 5 shows that the EELB-MEGA and EELB-EIGA consume minimum energy about 20 joules while varying number of nodes since it stores the best individuals in the memory. The related schemes consume much energy than proposed schemes. The objective of the proposed schemes is to deal with selecting cluster head with highest energy in the network. Itconsidered energy metric in DGA to balance the load for selecting cluster heads. The EIGA and MEGA found nodes with highest energy in each generation of the population. Then, the node with highest energy is selected as cluster head, and all its one hop neighbors are selected as cluster members with minimum deviation of neighboring nodes that make a stable cluster structure. The proposed schemes form optimal cluster and cluster head through MEGA, and energy is spent evenly to prolong the network lifetime. From Table 3, we can see that the proposed EIGA and MEGA schemes show pretty better performance in terms of the energy consumption while numbers of nodes are varied in thenetworks. In this analysis, EELB-MEGA and EELB-EIGA keeps minimal energy consumption to form clusters andits members.

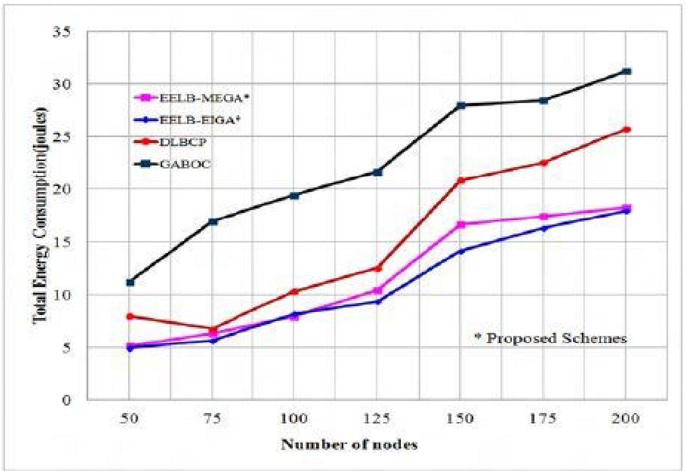


Figure 5: Total energy consumption vs Nodes

4.2. Packet delivery ratio

Figure 6 presents the packet delivery ratio(PDR) by varying the nodes in the network. The EELB-MEGA andEELB-EIGA schemes are compared with related schemes DLBCP and GABOC. The simulation time for each testwas 1000 sec. It shows that the proposed schemes are maintained higher PDR about 97%. The PDR of proposedschemes gets increased when the number of nodes increases. The related schemes achieve less PDR because theyare not focused on solving dynamic topology and multi-metric clustering problem in MANET. It shows that the PDRincreases for the proposed schemes since it considers energy metric and also stores the best individuals in memory toreduce complex computing process. EELB-EIGA gives better solution in dynamic network topology because it used an elite from previous population.

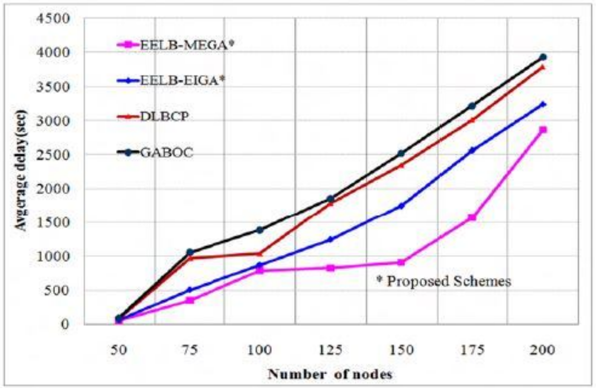


Figure: Delay vs Nodes

4.5. Average End-to-End delay

Figure 10 shows that the proposed scheme such as EELB-MEGA and EELB-EIGA achieves minimum delay forpacket forwarding because the proposed schemes selected the energy-efficient cluster heads for maintaining stabilitycluster structure. It makes load-balancing effectively for packet forwarding. In EIGA, elites are selected that can be used in future use and worst individuals are expelled from the set of optimal solutions. All selected elite'behave like excellent to form effective clusters. The proposed schemes achieved less delay about 2869msec to deliver thepackets. The proposed scheme increases average delay significantly when the number of nodes exceeds 150. Thegraph shows that the EELB-MEGA and EELB-EIGA outperforms the other related schemes because the proposedschemes provides minimum clustering cost and obtain a load-balancing to increase the network lifetime.

5. CONCLUSION

Naturally, load balancing is very much challenging to treat with the dynamic clustering problem in changing network topology in MANET. The dynamic genetic schemes such as EIGA and MEGA are used to address the DOP in MANET. The proposed system considered the distance and energy parameters to form clusters with the help of EIGA and MEGA schemes. EIGA and MEGA select the cluster heads with highest energy for maintaining the cluster structure and balance the load effectively. The proposed schemes used energy and distance metric for calculating the fitness function. Then, genetic operations are applied for selecting optimal clusters and cluster heads. It consumes minimum energy because MEGA store current environment into memory to future generation.The proposed EIGA and MEGA schemes earns a better performance than the existing schemes. The reason is that both the Elitism-based immigrant scheme and the memory scheme have utilized the similar idea to exploit the old useful information. In the memory scheme, the best individual is stored into the memory while in the Elitism-based immigrant scheme, the best individual is selected as the elitism. Therefore, EIGA and MEGA are suitable for the DLBCP. Simulation results show that the proposed EIGA and MEGA is analyzed for DOP in MANET. Compared with the existing protocols like DLBCP, GABOC, it consistently performs well with respect to the network lifetime, energy consumption of a node, packet delivery ratio, routing overhead and end-to-end delay. Future work may focus on preventing various attacks using genetic algorithm in networks that will be helpful to design a secure routing protocol.

REFERENCES

[1] Abin Paul and preethaK.G(2013). A Cluster Based Leader Election Algorithm for MANETs. International conference on control Communication and Computing,496–499.

[2] Hui Cheng and ShengxiangYang(2011). Genetic algorithms with elitism based immigrants for dynamic load balanced clustering problem immobile ad hoc networks. In Proceeding of IEEE Symposium on Computational Intelligence in Dynamic and Uncertain Environments(CIDUE),(pp.1–7).

[3] Sujatha K S, Dharmar V, Bhuvaneswaran R S.(2012).Design of genetic algorithm based IDS for MANET. In Proceeding of International Conference on Recent Trends In Information Technology (ICRTIT),(pp.28–33).

[4] ShengxiangYang ,Hui Cheng, Fang Wang.(2010). Genetic algorithms with immigrants and memory schemes for dynamic shortest path routing problems in mobile ad hoc networks. Journal of IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications andReviews,40(1),52–63.

[5] Siva Ram Murthy C ,Manoj B S.(2005). Ad Hoc Wireless Networks: Architectures and Protocols, Prentice Hall PTR.

[6] Anjum A, Mohammed, GihanNagib.(2012). Optimal Routing In Ad Hoc Network Using Genetic Algorithm .International Journal of Advanced Networking and Applications,3(5),1323–1328.

[7] HuiChenga, ShengxiangYangb, JiannongCao.(2013). Dynamic genetic algorithm for the dynamic load balanced clustering problem immobile ad hoc networks. Journal of Expert systems with applications,40(4),1381–1392.

[8] Bhaskar Nandi, Subhabrata Barman, SoumenPaul.(2010). Genetic Algorithm Based Optimization of Clustering in Adhoc Networks. International Journal of Computer Science and Information Security, 7(1),165–169.

[9] Bo Peng and Lei Li.(2012). A method for QoS Multicast Based on Genetic Simulated Annealing Algorithm. International journal of Future Generation Communication and Networking, 5(1),43–60.

[10] Ibukunola A, Modupea, Oludayo O, Olugbarab, AbiodunModupea.(2013).Minimizing Energy Consumption in Wireless Adhoc Networks with Meta heuristics. In Proceeding of 4th international conference on Ambient Systems, Networks and Technologies, 19,(pp.106–115).

[11] Perkins C E.(2001). Ad Hoc Networking, London: Addison-Wesley.

[12] Ting Lu ,Jie Zhu.(2013). Genetic Algorithm for Energy Efficient QoS Multicast Routing. IEEE Communications Letters, 17(1),31–34.

[13] Biradar A, Thool R C.(2014). Reliable genetic algorithm based intelligent routing for MANET. In proceedings of World Congress on ComputerApplications and Information Systems (WCCAIS), (pp. 1-8).

[14] Xu Li.(2005). Genetic Algorithm Simulated Annealing Based Clustering Strategy in MANET, Lecture Notes in Computer Science,3610,1121–1131.

[15] Hoda Hassan, Mohamed Eltoweissy.(2012). CORM: A reference model for future computer networks. Journal of Network and ComputerApplication,35(2),668–680.

[16] Wahabou A, Adrien H, Christelle B, Dominique D, Damien C, FranoisS(2011). Using an evolutionary algorithm to optimize the broadcastingmethods in mobile ad hoc networks.34(6),1794–1804.

[17] Gopalakrishnan Nair T R ,KavithaSooda, Yashoda M B(2011). Enhanced Genetic Algorithm approach for Solving Dynamic Shortest PathRouting Problems using Immigrants and Memory Schemes. In proceedings of International Conference on Frontiers of Computer Science.

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