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Energy Efficient Dynamic Load Balanced Clustering Protocol using Memory Enhanced Genetic Scheme and Elitism based Immigrant Genetic Scheme for MANET

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Mobile Ad hoc Network (MANET) is a kind of self configuring networks. 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. MANET can also be partitioned into clusters for maintaining the network structure. Generally, Clustering is used to reduce the size of topology and to accumulate the topology information. 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 effectively. In this work, we used dynamic genetic algorithms such as Elitism based Immigrants Genetic algorithm (EIGA) and Memory Enhanced Genetic Algorithm (MEGA) 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 increases 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: Adhoc Networks, Clustering, Dynamic load balancing, Elitism based Immigrant Genetic algorithm, Memory Enhanced Genetic Algorithm.

In a MANET, breaking of communication link is very frequent, as nodes are free to move to anywhere[1, 2]. The static routing path problem causes dynamic optimization problem in MANET. One of the most critical issues in MANET is the significant differences in term of processing and 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, scalability is more challenging in MANET[6]. So, MANET needs efficient clustered 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. Work in[4] used reliable genetic algorithm in routing during route discovery to get an optimum solution and 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

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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 provides 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 scheme[27], and Genetic based optimum routing[13] to enhance routing performance. However, the major disadvantage of these schemes doesn't perform well to node mobility and scalability. Previous research works focus on clustering where cluster heads are selected in the network. In this paper, the proposed scheme form clusters with optimal cluster heads. Moreover, cluster formation is based on the metrics such as node energy and node's degree. 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 (DLBCP) by the existing dynamic optimization problem.
- A genetic operation such as selection, fitness function, mutation and crossover applies for cluster head selection. Distance of nodes 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 a packet delivery ratio, routing overhead and total energy consumption of the network. The results show that MEGA out performs the EIGA.

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 in the network. Section 4 presents our simulation results and a relevant performance analysis. A section 5 presents our conclusions. Finally, Section 6 presents future direction.

Previous works

MANET has important characteristic in terms of topology dynamics due to node movement. 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. Work in[23] proposed two multi-populations 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. Work in[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.

The static shortest path (SP) problem is addressed by using intelligent optimization techniques[11]. The authors used GA by immigrants and memory schemes to solve the dynamic SP routing problem in MANET. They designed a mechanism of the standard GA and integrate the several immigrants and memory schemes to enhance routing performance in dynamic environment. These schemes are not applied to multicasting routing problem in a dynamic network environment. A Genetic Algorithm Based Optimization of Clustering (GABOC)[15] scheme focuses on implementation of weighted clustering algorithm with the help of GA to improve the performance of cluster head election procedure. It used the combined weight metrics such as cluster head degree, battery power, node mobility and distance to search dominant set. This scheme selects the minimum number of cluster heads that covered all the nodes. It does not provide an optimal solution when they decrease the transmission range because number of cluster heads increased. It consumes more energy when increases number of the cluster heads. An adaptive genetic simulated annealing scheme[16] presented for QoS multicast routing. This scheme combines GA and simulated annealing by randomly altering symbols of the chromosome and then making successive random modifications. For a large scale network, it is time consuming to obtain the optimal solution to the least cost QoS multicast routing problem. Work in[8] described a method to form the clusters in networks by using avoidance strategy. It neglects the dynamics of the sub networks during the leader election process. It also enhanced the performance of leadership election with respect to the network overhead. Topology tracing is done by flooding which consumes much of the network resources. They do not use the efficient scheme to trace the networks.

An energy efficient genetic algorithm[21] finds the delay constrained multicast tree to reduce the power consumption. It applies crossover and mutation operations on trees. The heuristic mutation technique can improve the total energy consumption of a multicast tree. This approach focuses only on source based routing trees but not on shared multicasting trees. An automatic cluster selection scheme[18] proposed to select efficient clusters using relative eigen value Quality. They designed a technique to minimize the multi way normalized cut, and also tried to simultaneously minimize the number of edges cut between clusters. It did not suitable for updating the clustering in a distributed manner as the network evolves over time. SAT/ILP techniques[20] solved the optimizing complex cluster formation in MANET. The objective of this scheme was to avoid the broadcasting storm problem with the minimum number of transmissions. The objective of the ILP formulation was to find the minimum set of connected cluster heads. It takes more time to find optimal solution as the network gets bigger. A loose virtual clustering based scheme[19] construct a hierarchical network and to avoid packet forwarding through high power nodes. It did not rely on geographic information using multi-channel and also not focused on energy issues. A geographic adaptive fidelity scheme[17] focused in saving energy consumption for entire network. They used Meta heuristic mechanism for solving convoluted optimization problems by mimicking the biological evolution of computing model. It did not perform well large scale network structure.

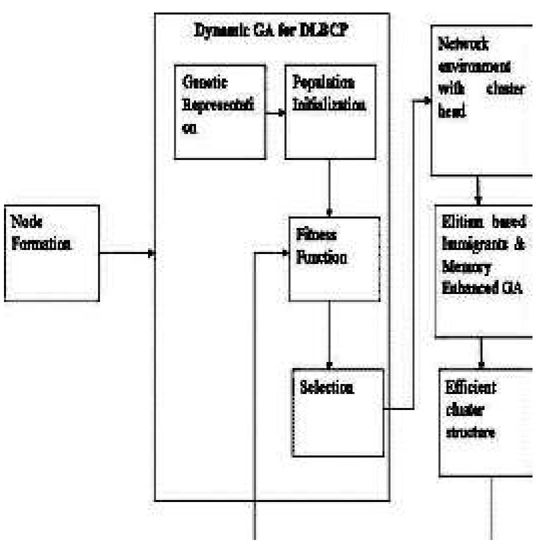

Fig. 1. Dynamic GA for proposed system

Proposed work

In MANET, 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 and energy metric. 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[25]. The memory based GA is used to store information about the old environments. By using these dynamic GA schemes, the efficient cluster structure with cluster head is obtained. Figure 1 shows that dynamic GA for the proposed system.

MANET is represented as a un-directed graph G (V_i, E_j), where V_i represents the set of wireless nodes and E_j represents the wireless links connecting two neighboring nodes. Cluster headset over a graph can be expressed as equation (1)

$$Ch_i \mid i \in \{1,2,...n\}, 1 > n < 30 \qquad ...(1)$$

Where *chi* is a cluster headset, *n* is the number of nodes in graph *G*(*Vi*, *Ej*). Each cluster head set in the network is given by equation(2)

$$CH_i = \{C_1, C_2, ...C_j\} \qquad ...(2)$$

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

$$\sigma_{CH\,i} = \sqrt{\frac{1}{A_m}\sum_{j=1}^{A_m}(DC_E - \overline{d_{CHi}})^2} \qquad ...(3)$$

Then, energy efficient node of each cluster is found. Energy of each node in a cluster determined as follows

$$E_t = E_{tx} + E_{rx} + E_{ideal} \qquad ...(4)$$

Where E_{tx} and E_{rx} is the energy consumed when the packet is transmitted and received. Then, we selected the minimum standard deviation node as well as the energy efficient node as a cluster head.

Genetic Representation

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

$$P = \{n_1, n_2........n_m\} \qquad ...(5)$$

Each node in network $\{n_1\},\{n_2\},...,\{n_m\}$ represents gene. Set of permutation nodes of network is represented as Chromosome. The permutations can be expressed as

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

where *n* represents the total number of nodes, *r* represents the elements taken from the

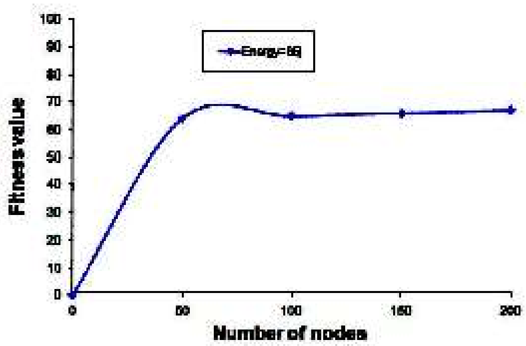

Fig. 2(a). Crossover for energy

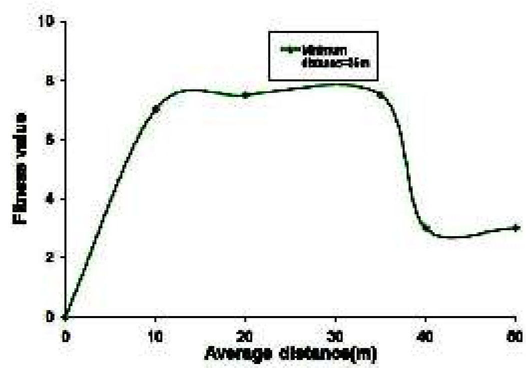

Fig. 2(b). Crossover for distance between nodes

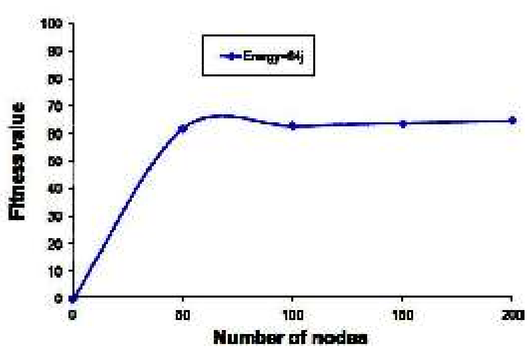

Fig. 3(a). Mutation for energy

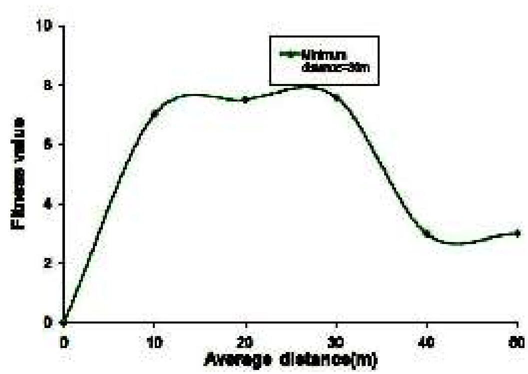

Fig. 3(b). Mutation for distance between nodes given set of n. It guarantees 115 that each chromosome has no duplicate node ID and investigates the dynamism of network topology.

Population Initialization

In a DGA, each chromosome corresponds to a potential solution. The random immigrant scheme generates a new best child into the population. 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 equation (7)

$$P_{GA} = \{Chr_o, Chr_1, \ldots, Chr_{q-1}\} \quad ...(7)$$

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 deviation as cluster head. If the current cluster head drawn much energy, another node with higher energy is allowed to become the cluster head. The fitness value of chromosome Chr_i represented as $F(Chr_i)$. It is calculated by equation (8)

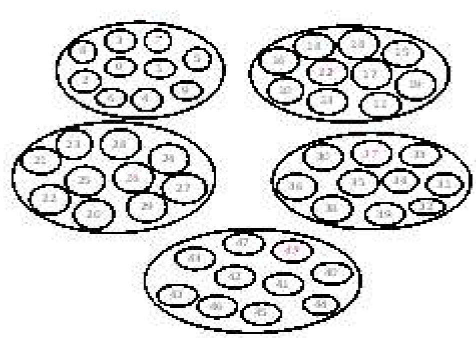

Fig. 4. Scenario of 50 nodes

Table 1. Routing table

D	nextHop	hopCount	GAF
S#	RREQ.S#	hop o& +1	1
D	nextHop	hopCount	GAF
S#	RREQ.S#	hop o& +1	0
D	nextHop	hopCount	GAF
S#	RREQ.S#	hop o& +1	-1

$$F(chr_i) = \frac{1}{\sqrt{\frac{1}{A_m}\sum_{j=1}^{A_m}(DC_E - \overline{d_{CHi}})^2}} \quad ...(8)$$

Then, optimal cluster heads are selected after applying the fitness function to chromosomes. It can be expressed as follows

$$F(chr_i)=\{CH_1,CH_{2,}\ldots\ldots..,CH_n\} \quad ...(9)$$

Selection

The proposed scheme used pairwise tournament selection approach[22] to improve quality of the population because high quality chromosomes alone pass to the next generation. Here, we implemented a pairwise tournament selection scheme 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 defined as the ratio of the probability of selection of the best chromosome in the population. The selection pressure is expected to average fitness of the population after selection. The probability of making the wrong decision increases exponentially when the selection pressure increases. Therefore, the pairwise tournament selection without replacement is employed for the proposed DGA schemes. Two chromosomes are picked and one among those

Table 2. Simulation environment

Parameter	Values
Simulation time	1000 sec
Simulation area	1000 × 1000
Transmission range	50m
Number of nodes	50,100,150,200
Threshold value	[0,1]
speed	[10-20] m/s
Packet size	512 bytes
Propagation	Two ray ground
Traffic source	Constant
Antenna	Omni directional
Mobility model	Random Mobility Model
Initial energy	100 joules
Transmitting energy	0.8 joules
Receiving energy	0.2 joules

selected as a fitter. However, the same chromosome should not be picked twice as a parent. It could get the number of nodes already selected by using fitness value. It is given by equation (10)

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

Crossover and Mutation

Genetic operators such as crossover and mutation[26] are used to generate children nodes. The Standard GA evolves a population of candidate solutions through selection and variation. New populations are generated by selecting suitable best individuals from the current population and then recombining them by using crossover and mutation to create new children. Crossover helps to generate two children chromosomes from two parent chromosomes. We used the X-Order1 method[12] to represent the genes in each children chromosome that are inherited from two parent chromosomes. Mutation uses gene swapping method for generating a children chromosome from a parent chromosome by changing the values of some genes. Mutation and cross over returns the best fitness value with respect to minimum distance between nodes and minimum remaining energy of individual nodes respectively. Mutation and cross over are performing the following equation (11) and (12) respectively.

$$Max(E_{res}) = \{c_1, c_2 \ldots c_j\} \quad ...(11)$$

$$d_{\min} = \{d_{1,1}, d_{1,2}, \ldots d_{i,j}\} \quad ...(12)$$

where c_j is cluster member and $d_{i,j}$ is the distance between node i and node j with in the clusters. The Figure 2(a) and 2(b) and figure 3(a) and 3(b) shows that the optimal values for energy and distance between nodes by applying crossover and mutation operation respectively that elected as cluster heads. The energy of 64 joules and a distance between nodes is 30m considered for fitness function that yields optimal solutions.

Table 3. Total energy consumption

Number of nodes	EIGA	MEGA
50	5.184	4 4.95
100	7.94	8.1666
150	16.65	4.146
200	18.27	17.956

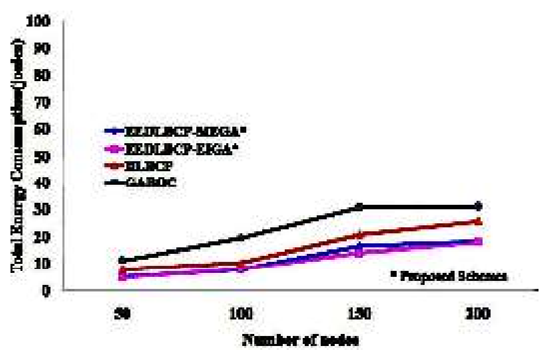

Fig. 5. Total energy consumption *Vs* nodes

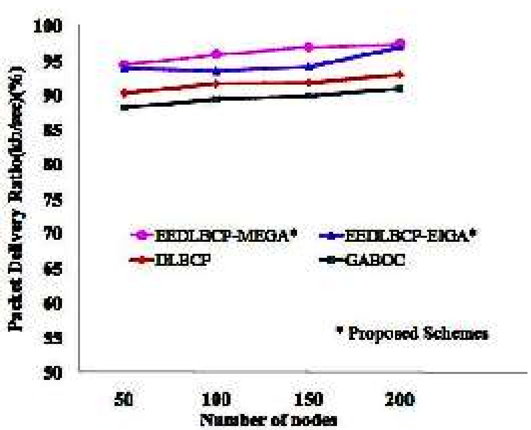

Fig. 6. Packet delivery ratio *Vs* nodes

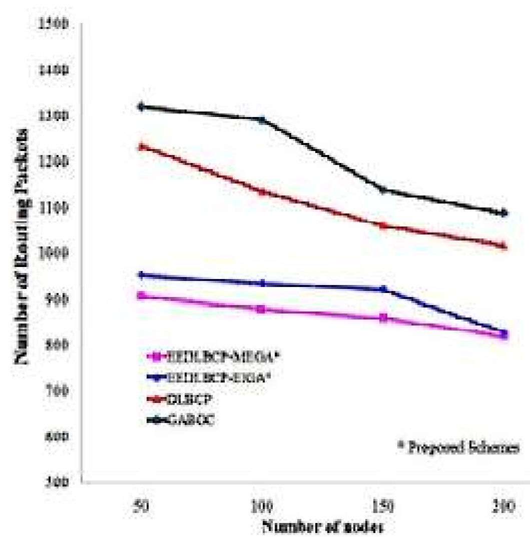

Fig. 7. Routing overhead *Vs* nodes

Elitism based immigrant scheme

We used an elitism based immigrant scheme to deal with DOP to perform well for the DLBCP. Selection and recombination operation took place in EIGA for each generation t. The elite E(t “ 1) from the previous generation is used as a base to create immigrants in which a set of best individuals is iteratively generated by mutating E(t “ 1) with a probability p^i_m. If the mutation probability p^i_m is satisfied in EIGA, the elite E(t”1) is used to generate the new immigrant, otherwise; E(t “ 1) itself used as a new immigrant. It uses the elite from previous population to guide the immigrants toward the current environment

Memory enhanced GA

MEGA stores latest information from the current environment to enhance 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 reused in new environments. Old solutions in a new environment reactivated in the explicit memory scheme when the current environment changes. The memory scheme is able to achieve the best solution with time going an old environment when the environment changes periodically, because it reappears remember the old environment. 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. Memory is needed to be updated either best individual from the current generation or elite from the previous generation replaced the random points still exists in the memory. In order to store the most relevant information about the changed environment in the memory, the memory is updated according to the population before the environmental changes. The best individual of the current population replaces one of them randomly for updating memory. MEGA uses a memory of size m = 0.1 “ n. The memory in MEGA is reevaluated every generation by detecting environmental changes. If the environment changes, one individual in the memory has been detected and changed its fitness value. Then, the memory is merged with the current population and the best n “m individuals are selected as an interim population. It performs

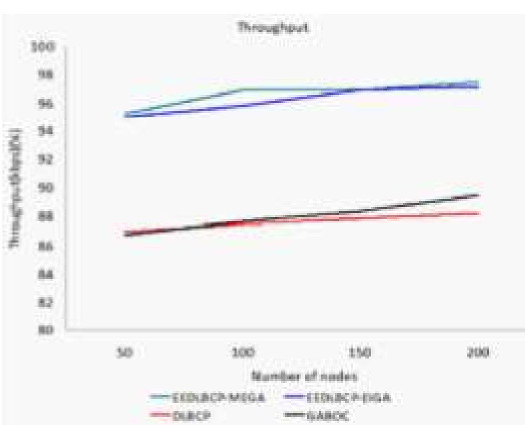

Fig. 8. Throughput *Vs* nodes

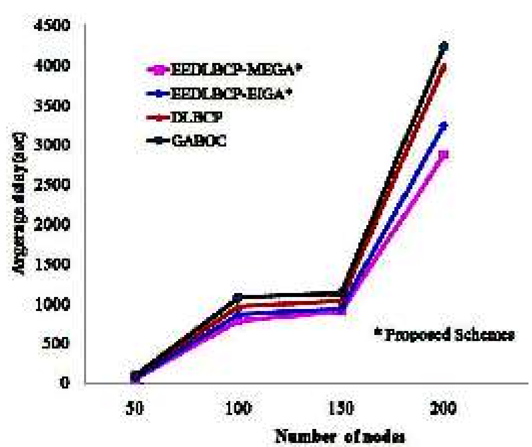

Fig. 9. Delay *Vs* nodes

genetic operations for a new population, while the memory remains unchanged.

Algorithm for MEGA

t:=0, t_M := rand(5,10), E_T = 1 joules and $d_{i,j}$ =30m
randomly initialize population P(0) and memory M(0)
repeat
evaluate population P(t) and memory M(t)
replace the worst individual in P(t) by the elite E(t-1) from P(t-1)
Elite'(t-1) =(Elite(t-1)) > E_T < $d_{i,j}$
If change detected then
P''(t) := retrieve Best Members From (P(t), M(t))
Else P'(t) := P(t)
// time to update memory
If t= t_M || change detected then
If t = t_M then
B_p(t) := retrieve best member from (P'(t))
If change detected then B_p(t) := E'(t-1)
If still any random point in memory then,
replace a random point in memory with B_p(t)
else
If t=t_M then
Find the memory point C_M(t) closest to B_p(t)
If f(B_p(t)) > f(C_M(t)) then
C_M(t) := B_p(t)
T_M := t+rand(5,10)
// standard genetic operations
P''(t) := select for reproduction (P'(t))
Crossover(P''(t),p_c)
Mutate(P''(t),p_m)
P(t+1) := P"(t)
Until the termination condition is met (t > t_{max})

Where,
P(t) and m(t) are the population and memory respectively
P'(t) is the best member which is retrieved from p(t) and m(t)
B_p(t) is the best member which is retrieved from P'(t)
C_M(t) is the memory point closest to B_p(t)

The MEGA scheme initialized memory randomly and updating in a stochastic pattern. After each memory updating, a random integer in between 5 to 10 is generated to decide the next memory updating time t_M which is calculated by using $t_M = t + rand(5, 10)$. According to the population, the memory is also updated before the environmental change. The memory $m(t)$, population $p(t)$, time(t), total energy(E_T), and memory updating time(t_M) are initialized. Population p(0) and memory m(0) is randomly assigned. $p(t)$ and $m(t)$ is evaluated by using MEGA for replacing worst individuals by $E(t$ " 1) in previous population. If the probability p^i_m is satisfied, the elite $E(t$ " 1) generate the new immigrants by using mutation operation. Otherwise E (t"1) itself used as a new immigrant. *Elite*2 (t"1) produce an individual that has the highest energy. The best members from p (t) and m (t) is retrieved when the environmental change is detected that assigns to P2 (t), otherwise; $p(t)$ assign to P2 (t). If there is any change and the time (t) is equal to the updating time (t_M), then the best member from P2 (t) is retrieved and is assigned to $B_p(t)$. Random point in memory is replaced with $B_p(t)$ if there is a change and $B_p(t)$ is equal to E2 (t " 1); otherwise the most similar point is replaced. The memory pointed $C_M(t)$ closest to $B_p(t)$is obtained by giving $t = t_M$ condition. $C_M(t)$is assigned to $B_p(t)$ when $B_p(t)$ is greater than $C_M(t)$. p2 2 (t) is obtained by using the standard genetic operation. The space taken by the proposed algorithm is O (1) constant space with respect to the input size. It stores only flag of GA (GAF). It's stored in the routing table of the network.

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

RESULTS AND DISCUSSION

The proposed scheme has been implemented in network simulator (NS2). The main objective of the simulation was to enhance energy efficiency to increase the network lifetime. 100 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 followed the random way point model[28] that finds the availability of connection paths in MANET. 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 structure. The proposed schemes also evaluated by comparing it with the related DLBCP and GABOC schemes in terms of the packet delivery ratio, energy consumption, throughput and routing overhead. The simulation results were studied by varying the network size from 50 to 200. We have integrated Elite based immigrant and Enhanced memory based immigrant scheme to update a latest information about the environment.

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. In this, the node 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. DGA selects an energy efficient cluster head by considering the distance and energy of each node in the network. The elected cluster head transmits the data to its neighboring nodes and those nodes are considered as its cluster members. Figure 4 shown that the node 7 is elected as the cluster head and it is transmitting the data to its neighbor nodes 0,2,1,3,4,5,6,8,9 and these are considered as the cluster members of node 7. Likewise other cluster structures are also formed. After the environment change because of node 7 moves its transmission. EIGA generates a new population and MEGA provides an old environment for forming a cluster structure that reduces complexity.

Total Energy Consumption

The Figure 5 is plotted across the number of nodes and the total energy consumption of various nodes. Figure5 shows that the EEDLBCP-MEGA and EEDLBCP-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 to the node with highest energy in the network. It considered 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.

Table 3 shows that analysis of total energy consumption of proposed schemes while numbers of nodes are varied in the networks. In this analysis, EEDLBCP-MEGA and EEDLBCP-EIGA keeps minimal energy consumption to form clusters and its members.

Packet delivery ratio

Figure 6 shows the packet delivery ratio (PDR) by varying the nodes in the network. The EEDLBCP-MEGA and EEDLBCP-EIGA schemes are compared with related schemes DLBCP and GABOC. The simulation time for each test was 1000 sec. It shows that the proposed schemes are maintained higher PDR about 97%. The PDR of proposed schemes get increased when the number of nodes increases. The related schemes achieved less PDR because they are not focused on solving dynamic topology and multi metric clustering problem in MANET. It shows that the PDR increases for the proposed model since it considered energy metric and also stores, the best individuals in memory to reduce complex computing process.

Routing Overhead

In this simulation, the routing overhead is evaluated for EEDLBCP-MEGA, EEDLBCP-EIGA, DLBCP and GABOC while varying the number of nodes. Figure 7 shows that the routing overhead caused by EEDLBCP-MEGA and EEDLBCP-EIGA is less than that of the other two related schemes. EEDLBCP-MEGA and EEDLBCP-EIGA caused minimal routing overhead about 30% and 35% respectively because EEDLBCP-MEGA stored current environment into memory to future generation. EEDLBCP-EIGA scheme used previous generation for future use. It is clearly noticed that the routing overhead decreases in the proposed scheme because worst individuals are replaced with best suitable individuals that are generated by elite in previous population. The proposed schemes also used old environment that stored in memory for reducing routing overhead.

Throughput

Figure 8 shows the throughput for EEDLBCP-MEGA, EEDLBCP-EIGA and related schemes when the number of nodes varied. Throughput is defined as the number of packets, delivered to destination successfully that determine performance of the network. It was shown that the performance of the proposed scheme is more efficient than the related schemes. EEDLBCP-MEGA and EEDLBCP-EIGA schemes achieve higher throughput than related schemes because it considers load balance metric to maintain stable cluster structure. The related schemes not achieved mark able throughput because it is not considered energy metric to form cluster heads. Therefore, the proposed schemes prolong the network lifetime.

Average End to End Delay

Figure 9 show that the proposed schemes such as EEDLBCP-MEGA and EEDLBCP-EIGA achievable minimum delay for packet forwarding. Because the proposed schemes selected the energy efficient cluster heads for maintaining stable cluster structure. It makes load balancing effectively for packet forwarding. 300 The graph shows that the EEDLBCP-MEGA and EEDLBCP-EIGA outperform other related schemes because the proposed schemes provides minimum clustering cost and obtain a load balancing to increase the network lifetime.

CONCLUSION

Naturally, it is very much challenging to treat with the dynamic clustering problem in changing network topology in MANET. We used the dynamic handling schemes such as EIGA and MEGA addressed 305 the DOP in MANET. The proposed schemes 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 and then applied genetic operation for selecting optimal clusters and cluster heads. It consumes minimum energy because EEDLBCP-MEGA store current environment into memory to future generation. We earned a better performance and achieved an efficiency of EIGA and MEGA and also been verified with the related schemes. Simulation results show that the EIGA and MEGA are analyzed for DOP in MANET. We believe that this is the first work to examine the efficiency of EIGA and MEGA for solving the Dynamic Load Balancing Clustering Problem in MANET. Future work may focus on preventing various attacks using genetic algorithm in networks that will be helpful to design a secure routing protocol.

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