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RESEARCH PAPER

Load Balanced Clustering Technique in MANET using Genetic Algorithms

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ABSTRACT

Mobile adhoc network (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 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 load -balancing in 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 and EIGA give a better performance in terms of load-balancing.

Keywords: Clustering, genetic algorithm, load-balancing, mobile adhoc networks

1. INTRODUCTION

In a mobile adhoc network (MANET), breaking of communication link is very frequent, as nodes are free to move to anywhere. The static routing path problem causes dynamic optimisation 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. 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. Reliable genetic algorithm[2] used in routing during route discovery to get an optimum solution and route maintenance. Cluster based routing provides a optimal result in a network topology structure[3,5]. Various techniques have been introduced such shortest path routing[11,12], energy- efficient QoS multicast routing[1], energy- efficient multi-metric QoS routing scheme[16], and Genetic based optimum routing[8] to enhance routing performance in the network. However, these schemes did not perform well to node mobility and scalability.

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Recent researchers, several cluster-based mechanisms have been proposed that are introduced in the literature. In order to achieve fairness and uniform energy consumption, an efficient clustering scheme produces a load-balanced cluster head to adapt topology dynamics. DLBCP[4] 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. The output is the standard deviation of cluster head degrees calculated from the cluster heads represented by the individual. It is unable to address the dynamic multi-metric clustering problem. The interaction between multiple populations brings an extra time overhead. This scheme is more complicated due to the extra control message used in the clustering process.

The static shortest path problem is addressed by using intelligent optimisation techniques[6]. The authors used GA by immigrants and memory schemes to solve the dynamic shortest path routing problem in MANET. These schemes are not applied to multicasting routing problem in a dynamic network environment. A genetic algorithm based optimisation of clustering (GABOC)[15] used a weighted clustering algorithm with the help of GA to improve the performance of cluster head selection procedure. It does not provide an optimal solution when they decrease the transmission range because the number of cluster heads increased. It consumes more energy when the number of the cluster heads increases. It does not pay much attention to the continuous topology changes, which are actually the inherent characteristics of MANET.

An automatic cluster selection scheme[10] selects an efficient clusters using relative eigen value Quality. It did not suitable for updating the clustering in a distributed manner as the network evolves over time. SAT/ILP techniques[12] solved the optimizing complex cluster formation in MANET. It takes more time to find optimal solution as the network gets bigger. A loose virtual clustering based scheme[11] 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[9] focused in saving energy consumption for entire network. They used meta-heuristic mechanism for solving convoluted optimisation problems by mimicking the biological evolution of computing model. It did not perform well large scale network structure. An energy-efficient genetic algorithm[13] finds the delay constrained multicast tree to reduce the power consumption. This approach focuses only on source based routing trees but not on shared multicasting trees. Multi-populations GAs[14] such as forking GA and shifting balance GA. Both are enhanced by an immigrants scheme to hold the dynamic optimisation problem. It is consumed more energy to handle control messages during network topology changes.

The proposed scheme form 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 minimum distance is selected as cluster head. The MEGA scheme aims to improve the performance of GAs for dynamic optimisation problems (DOP). It stores recent information from the current environment. Then, the stored information can be reused in new environments to reduce overhead. The design goal of the proposed schemes is to develop an energy-efficient clustering structure. The proposed scheme increases the lifetime of the network. The objective of the proposed schemes is to find the optimal set of clusters with cluster heads for solving dynamic optimisation problem.

2. PROPOSED WORK

In MANET, an effective clustering algorithm adapts to topology change. Load-balanced clustering mechanism (LBCM-MEGA) and load-balanced clustering mechanism (LBCM-EIGA) produces the new load-balanced clusters and cluster heads to increase the network lifetime. 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. By using these dynamic GA schemes, the efficient cluster structure with cluster head is obtained. Figure 1 shows the proposed load-balanced clustering technique for MANET.

MANET is represented as an 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 neighbouring nodes. Cluster heads over a graph can be expressed as

$$ch_i \,|i \in \{1,2,\ldots n\}, 1 > n < 30 \tag{1}$$

where ch_i is a cluster headset, n is the number of nodes in graph

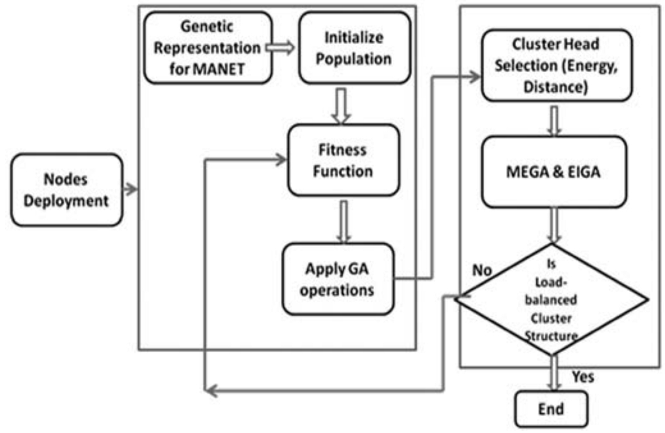

Figure 1. Proposed load-balanced clustering technique.

$G(V_i, E_j)$. Each cluster head set in the network is given by

$$CH_i = \{ C_1 , C_2 \ldots. C_j \} \tag{2}$$

The cluster head degree is a node with highest energy which is denoted as DC_E, d_{CHi}, is the average number of cluster members served by each cluster head and A_m is the average number of nodes served by each cluster head. This scheme aims to reduce the standard deviation of cluster members which is given by Eqn. (3) and Eqn. (4)

$$\sigma_{CHi} = \sqrt{\frac{1}{A_m} \sum_{j=1}^{A_m} (DC_E - \overline{d_{CHi}})^2} \tag{3}$$

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

$$E_T = E_{tx} + E_{rx} + E_{ideal} \tag{4}$$

where E_{tx} and E_{rx} are the energy consumed when the packet is transmitted and received. E_T is the total energy and E_{ideal} is the ideal energy of a node. Then, the minimum standard deviation node as well as the energy-efficient node as a cluster head is selected.

2.1 Genetic Representation

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

$$P = \{ n_1, n_2, \ldots. n_m \} \tag{5}$$

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

$$np_r = n!/(n\text{-}r)! \tag{6}$$

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.

2.2 Population Initialisation

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 P_{GA} 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 Eqn. (7)

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

2.3 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 leads 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 draws much energy, another node with higher energy is allowed to become the cluster head. The fitness value of chromosome chr_i is represented as $F(chr_i)$. It is calculated by Eqn. (8)

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

Then, optimal cluster heads are selected after applying the fitness function to chromosomes.

$$F(chr_i)=\{CH_1, CH_2 \ldots CH_n\} \quad (9)$$

2.4 Selection

The proposed scheme used pair-wise tournament selection approach to improve the quality of the population because high quality chromosomes alone pass to the next generation. Here, a pair-wise 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. 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 pair-wise tournament selection without replacement is employed for the proposed DGA schemes. Two chromosomes are picked and one among those is 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 Eqn. (10)

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

2.5 Crossover and Mutation

New populations are generated by selecting suitable best individuals from the current population and then recombining them by using crossover and mutation[16] to create new children. Crossover helps to generate two children chromosomes 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 crossover return the best fitness value with respect to minimum distance between nodes and maximum remaining residual energy of individual nodes respectively. Mutation and crossover are expressed in Eqn. (11) and Eqn. (12), respectively

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

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

where c_j is cluster member, $\mathrm{Max}(E_{res})$ is the maximum remaining residual energy of nodes within the cluster, and $d_{\min}$ is the minimum distance of node i and node j within the clusters. The proposed scheme considers the population size as varied such as 50,100,150, 200 and maximum number of generations as 15. The MEGA converges when the maximum number of generations is reached, and it had the best fitness value for energy and distance of the nodes. This fitness value of the chromosome showed the best optimal path selection to route the packets. Figures 2 - 5 shows that the optimal values for energy and distance between nodes to select cluster heads by applying crossover and mutation operation, respectively. The energy of 6.4 j and a distance between nodes 30m are considered for fitness function that yields optimal solutions.

2.6 Elitism-based Immigrant Scheme

An Elitism-based immigrant scheme is used 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

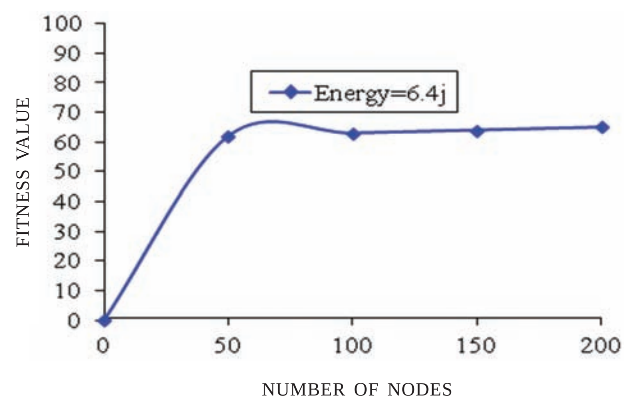

Figure 2. Crossover for energy.

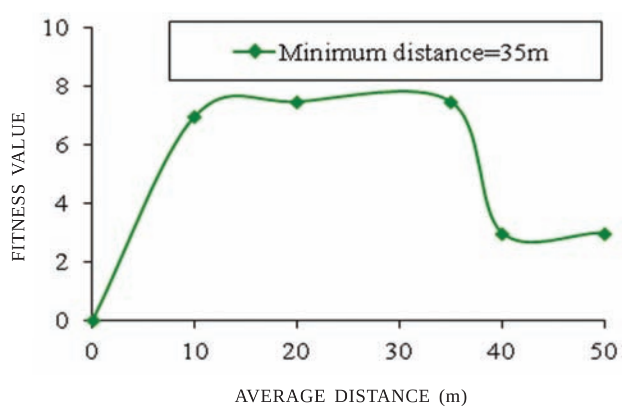

Figure 3. Crossover for distance between nodes.

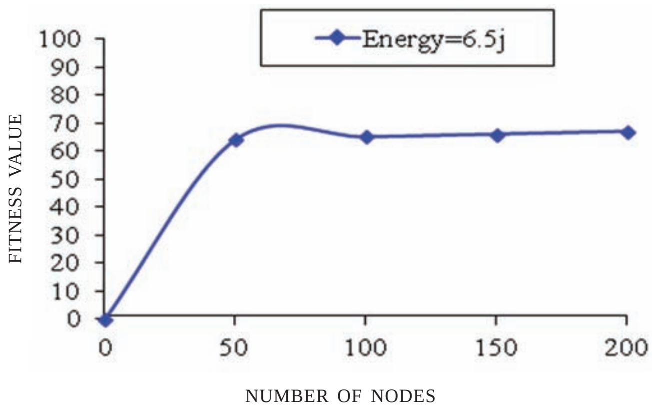

Figure 4. Mutation for energy.

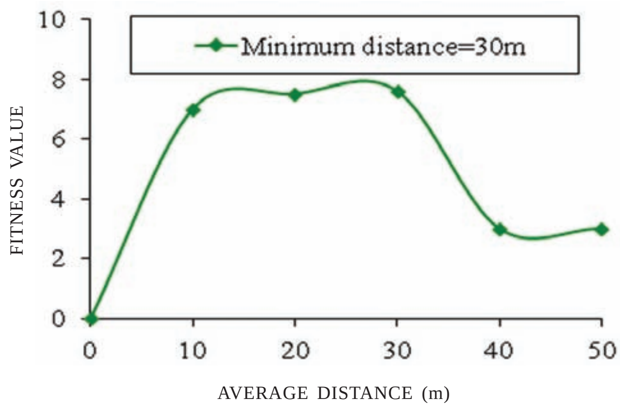

Figure 5. Mutation for distance between nodes.

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 is used as a new immigrant. It uses the elite from the previous population to guide the immigrants toward the current environment.

2.7 Memory-Enhanced Genetic Algorithm

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 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 existing in the memory. The best individual of the current population replaces one of them randomly for updating memory. A MEGA uses a memory of size m = 0.1 x n. The memory in MEGA reevaluated every generation by detecting environmental changes. The fitness value is changed if the environment changes and one individual in the memory have been detected. Then, the memory is merged with the current population and the best n - m individuals are selected as interim population.

Algorithm for MEGA

t:=0, t_M := rand(5,10), E_T = 1 joules and $d_{i,j}$=30 m
randomly initialise population $P(0)$ and memory $M(0)$
repeat
    evaluate population $P(t)$ and memory M(i)
    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 environment change detected then
    P'' (t) := retrieve best members from ($P(t)$, M (t))
Else P' (t):= P (t)
If t= t_M || change detected then // time to update memory
If t = t_M then
    $B_p(t)$:= retrieve best member from (P' (t))
If environment 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)
    $P''(t)$:= select for reproduction ($P'(t)$) // standard genetic operations
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 $p(t)$, $M(t)$ and $B_p(t)$ 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 initialised memory randomly updating in a stochastic pattern. After each memory updating, a random integer in [5, 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 initialised. Population P(0) and memory

$M(0)$ are randomly assigned. $p(t)$ and $m(t)$ are evaluated by using MEGA for replacing worst individuals by $E(t-1)$ in the previous population. If the probability P^i_m is satisfied, the elite $E(t-1)$ generates the new immigrants by using mutation operation. Otherwise, $E(t-1)$ itself is used as a new immigrant. Elite′ $(t-1)$ produces an individual that has the highest energy. The best members from $P(t)$ and $M(t)$ are retrieved when the environmental change is detected that assigns to $P'(t)$; otherwise, $P(t)$ is assigned to $P'(t)$. If there is any change and the time (t) is equal to the updating time (t_M), then the best member from $P'(t)$ 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 $E'(t-1)$; 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 $C_M(t)$. $P''(t)$ 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 the flag of GA (GAF). It is stored in the routing Table 1 of the network.

Table 1. Routing table

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

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 -1 indicates that the node has left the network. It means that the network topology was changed.

3. SIMULATION AND RESULTS

3.1 Simulation Study

The proposed scheme has been implemented in network simulator (NS2). Table 2 shows the parameter setting for simulation. Nodes are followed the random way point model[18] that finds the availability of connection paths in MANET. The proposed system analysed 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.

Table 2. Parameter settings for simulation

Parameter	Values
Simulation time	1000 s
Simulation area	1000 × 1000
Transmission range	50 m
Number of nodes	200, 500
t_M	[5,10]
speed	[10-30] m/s
Packet size	512 bytes
Propagation	Two ray ground
Traffic source	Constant
Antenna	Omni directional
Mobility model	Random way point model
Initial energy	10 joules
Transmitting energy	0.8 joules
Receiving energy	0.2 joules

3.2 Results and Discussion

The proposed scheme is also evaluated by comparing it with the related DLBCP and GABOC schemes in terms of the packet delivery ratio, energy consumption and routing overhead. The simulation results were studied by varying the network size from 50 to 500.

3.2.1 Energy Consumption of the Network

Figure 6 is plotted across the number of nodes and the total energy consumption of various nodes. Figure 6 show that the MEGA and EIGA consume minimum energy about 18 joules while varying the number of nodes since it stores the best individuals in the memory. The related schemes consume more energy than the 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 neighbours are selected as cluster members with minimum deviation of neighbouring nodes that make a stable cluster structure.

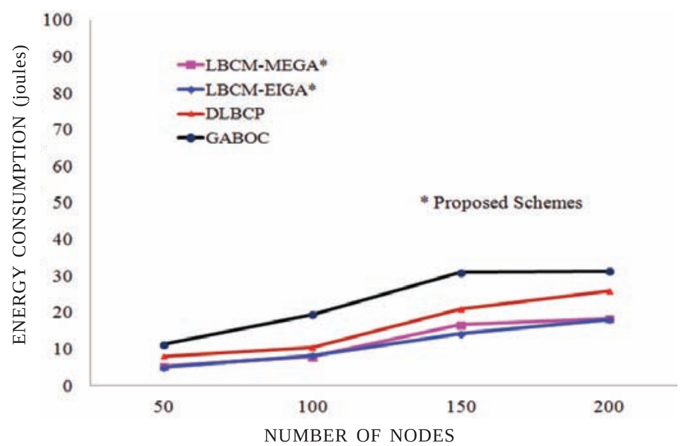

Figure 6. Energy consumption of the network.

Table 3 shows analysis of the total energy consumption of the proposed schemes while number of nodes is varied in the networks. In this analysis, MEGA and EIGA keep minimal energy consumption to form load-balanced clusters and their member.

Table 3. Energy consumption of the network

Number of nodes	EIGA	MEGA
50	5.184	4. 495
100	7.94	8.1666
150	16.65	14.6
200	18.27	17.956

3.2.2 Packet Delivery Ratio

Figure 7 shows packet delivery ratio (PDR) by varying the nodes in the network. The LBCM-MEGA and LBCM-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 maintain higher PDR about 97 per cent. The PDR of the proposed schemes gets increased when the number of nodes increases. The related schemes achieve 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 considers energy metric and also stores the best individuals in memory to reduce complex computing process.

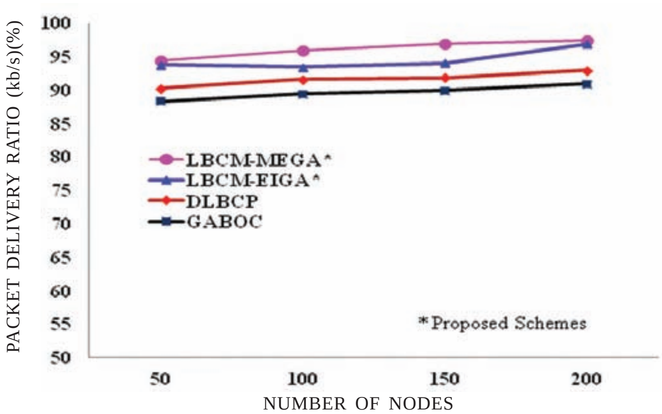

Figure 7. Packet delivery ratio.

3.2.3 Routing Overhead

The routing overhead is evaluated for LBCM-MEGA, LBCM-EIGA, DLBCP and GABOC while varying the number of nodes. Figure 8 shows that the routing overhead caused by LBCM-MEGA and LBCM-EIGA are less than that of the other two related schemes. LBCM-MEGA and LBCM-EIGA caused minimal routing overhead about 30 per cent because MEGA stored current environment into memory to future generation. EIGA scheme used previous generation for future use. The graph shows that the proposed schemes achieved less routing overhead than related schemes because worst individuals are replaced with best suitable individuals that are generated by elite in the previous population. The proposed schemes also used old environment that stored in memory for reducing routing overhead.

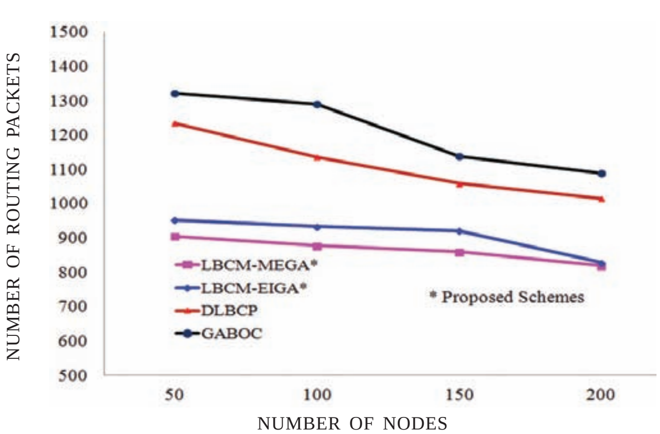

Figure 8. Routing overhead.

3.2.4 Average Delay

Figure 9 shows that the proposed scheme LBCM-MEGA and LBCM-EIGA achieves minimum delay for packet forwarding because the proposed schemes selected the energy-efficient cluster heads for maintaining stable cluster structure. It makes effective load-balancing for packet forwarding. The proposed scheme achieved less delay about 2869 ms to deliver the packets. The proposed scheme increases average delay significantly when the number of node exceeds 150. The proposed scheme outperforms than other related schemes because the proposed schemes provides minimum clustering cost and obtain a load-balancing to increase the network lifetime.

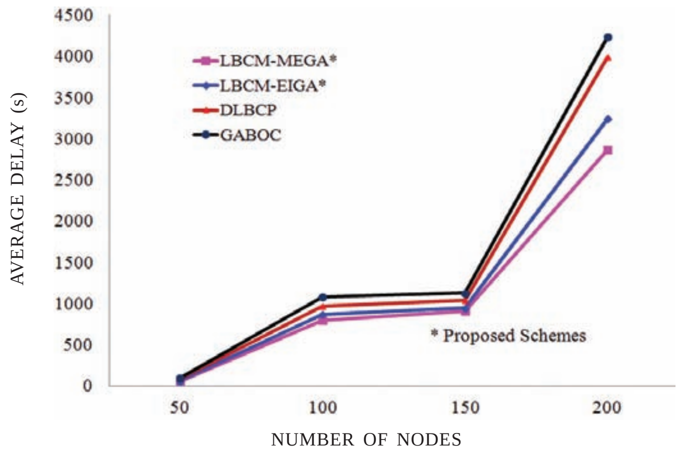

Figure 9. Average delay.

3.2.5 Network Lifetime

Figure 10 shows the network lifetime as a varied number of nodes. The lifetime increases as the number of nodes grow. Lifetime increase because MANET has to cover minimum required nodes to involve the clustering process, and far away nodes did not participate in the clustering process. The proposed scheme achieved 93 per cent of network lifetime. The proposed scheme uses an MEGA that increases the lifetime involved in the clustering process. This scheme used optimal energy and distance between nodes that avoid link breakage caused due to node movement. Energy is uniformly drained from all the nodes, and hence the network lifetime is significantly increased. This shows the effectiveness of the

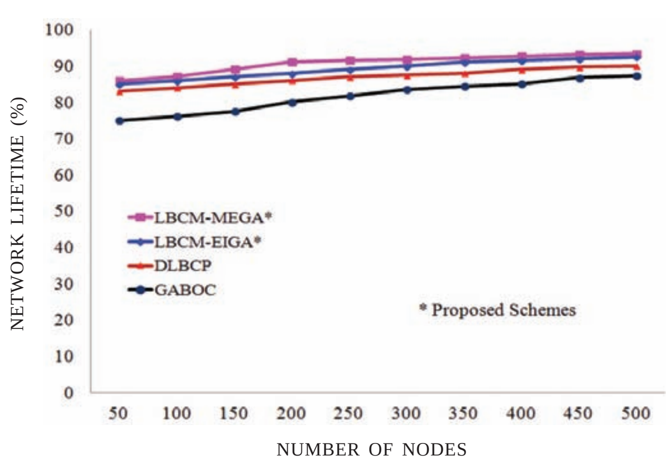

Figure 10. Network lifetime.

proposed scheme in extending the network lifetime. The related schemes decreased network lifetime due to the extra energy spent in generating the routing packets and control packets to maintain the clustering structure.

In the related schemes, extra energy is spent due to generating control packets and routing packets. And also, the related schemes are not considering multi metric to forms clustering process. The proposed scheme form optimal cluster and cluster head through MEGA, and energy is spent evenly to prolong the network lifetime.

3.2.6 Clustering Overhead

In this simulation, the clustering overhead is measured resulting from LBCM-MEGA and LBCM-EIGA, DLBCP and GABOC while varying mobility speed from 10 to 50 m/s in the network. The number of nodes is set to 500. Figure 11 shows the minimal clustering overhead caused by LBCM-MEGA and LBCM-EIGA. The clustering overhead of MEGA and EIGA schemes are approximately 30 per cent of the network traffic when the mobility speed is 50m/s, because the proposed schemes provides scalable and load-balanced clustering structure that exchange less control routing packets to form clusters.

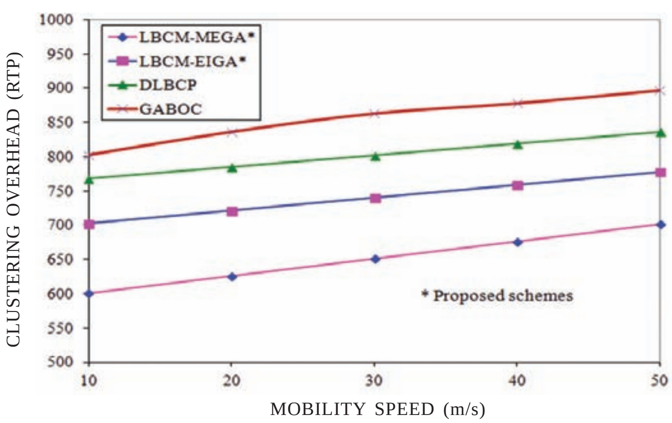

Figure 11. Clustering overhead.

4. CONCLUSION

Naturally, it is very much challenging to treat with the dynamic clustering problem in changing network topology in MANET. The dynamic handling schemes such as EIGA and MEGA are used to address 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. The proposed scheme earns a better performance. The reason is that both the MEGA and EIGA schemes have utilised the similar idea to exploit the old useful information. In the memory scheme, the best individual is put into the memory while in the elitism-based immigrant scheme the best individual is selected as the elitism, both for producing other individuals. 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.

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