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Glowworm Swarm Optimization based Clustered on – Demand Load Balancing Scheme (GSO-COD-LBS) for Heterogeneous Mobile Ad hoc Networks

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Abstract- Obtaining quality of service (QoS) through several routing schemes attracts researchers in the field of MANETs. Optimized routing through energy aware load balanced schemes is plays a significant role in ensuring QoS as well as many real – time applications. In this phase of research work, Glowworm Swarm Optimization is used for performing clustering operation. An adaptive on – demand routing mechanism is also employed. Simulation settings are used for analyzing the performance of the GSO-COD-LBS with other routing protocols / solutions / schemes using the metrics packet delivery ratio, throughput, packets drop, overhead and delay. From the results that are obtained through simulations it is inferred that GSO-COD-LBS outperforms other existing routing protocols and our earlier proposed works.

Keywords- routing, load balancing, energy, QoS, MANET.

I. INTRODUCTION

A Mobile Ad-hoc Network (MANET) is infrastructure lessnetwork which is collection of moving nodes connecteddynamically in arbitrary manner. Organizing and controllingoperations of the network are distributed among the nodesthemselves. The whole network is mobile, and the individualnodes are allowed to move freely. Every node in MANETscould be router. The nodes which may not connect directlyforward the packets using intermediate nodes so that thepackets can be delivered to their destinations. Multi-hopforwarding concept increased the degree of connectivity andminimize the energy consumption. The initialapplications of MANETs are military and emergency reliefoperations, later, they have attracted researchers since flexibleand efficient networks are needed in many others applications.In MANETs, the path/route which is a sequence of mobilenodes send data packets from a given source to thedestination.

Load balancing has been the focal point of numerous kinds of research including ad hoc networks. As load balancing is a system wide optimization and improvement component, the arrangements including this zone has for the most part been executed in the system layer of the OSI (Open Systems Interconnection) model. Routing protocols, as system layer operators, are in charge of calculation of the system network chart (considering the cost/advantage measurements) which would make them the most appropriate possibility to suit load balancing procedures. By taking load balancing procedures in the courses mentioned by the hubs in the system, a base worthy QoS can be ensured in the whole system. In ad hoc networks, routing protocols work in a circulated way inside every hub with no immediate associations among them. Given that plan of routing protocols depends on a conveyed paradigm, load balancing calculations need to work under some similar system suppositions. Therefore, accomplishment of a general system increase would be amazingly testing.

The paper is organized as follows. This section briefly introduces the problem statement. Section 2 discusses on related works carried out in the area of load balancing. Section 3 presents the proposed GSO-COD-LBS. Section 4 showcases the simulation settings along with the performance metrics. Section 5 portrays the simulation outcomes as results and discussions. Section 6 provides concluding remarks to the manuscript.

II. RELATED WORKS

Hui et al. (2012) proposed two multi-population GAs such as forking GA and shifting balance GA. Both are enhanced by an immigrant’s scheme to hold the dynamic optimization problem. It is consumed more energy to handle control messages during network topology changes. Hui et al. (2013) 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.

Sheng xiang et al. (2010) addressed the static shortest path (SP) problem using intelligent optimization techniques. They 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 dynamic network environments. Bhaskar et al. (2010) proposed a Genetic Algorithm-Based Optimization of Clustering (GABOC) that concentrated 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.

Bo and Lei (2012) presented an adaptive genetic simulated annealing algorithm for QoS multicast routing. This scheme combines GA and simulated annealing by randomly altering symbols of the chromosome. For a large scale network, it is time consuming to obtain the optimal solution to the least cost QoS multicast routing problem. Abin and Preetha (2013) 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 the 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.

Ting and Jie (2013) proposed an energy-efficient genetic algorithm to find the delay constrained multicast tree to reduce the power consumption. It applies crossover and mutation operations on trees. The heuristic mutation technique improves the total energy consumption of a multicast tree. This approach focuses only on source-based routing trees but not on shared multicasting trees. John et al. (2013) developed a scheme for determining the number of clusters by using relative eigen value quality. They also designed a technique to minimize the multi-way normalized cut, also tries 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. Cluster based Weighted Compressive Data Aggregation reduces the energy consumption in Wireless Sensor Network. It used The Weighted Compressive Data Aggregation algorithm (Samaneh and Jamshid, 2016) to each cluster to reduce the nodes involvement in routing. It raises the context switching overhead for higher catch hit.

Syed Zohaib et al. (2013) proposed the SAT/ILP Techniques for optimizing complex cluster formation in MANET. The objective of this scheme was to avoid the broadcasting storm problem with minimum number of transmissions. ILP finds the minimum set of connected cluster heads. It takes more time to find optimal solution as the network gets bigger. Peng et al. (2013) developed a virtual cluster-based scheme to construct a hierarchical network and avoid packet forwarding through high power nodes. It did not rely on geographic information using multi-channel and also not focused on energy issues. Ibukunola et al. (2013) described a geographic adaptive fidelity scheme for reducing energy consumption in MANET. They used meta heuristic mechanism for solving convoluted optimization problems by mimicking the biological evolution of computing model. It does not perform well with large scale network structure. Administrative Cluster-Based Cooperative caching scheme (El Khawaga et al., 2016) used cooperative caching strategy to keep at most two copies of the cached data items in each cluster. It needs additional administrative module to control the caching mechanism.

III. PROPOSED WORK

Glowworm swarm optimization (GSO) is an intelligent swarm optimization algorithm simulating the luminescent characteristics of fireflies. In the GSO algorithm, the algorithm models glowworm swarms scattered in the solution space and the fluorescence intensities are related to the fitness function of each glowworm's position. The stronger the glowworm brightness is, the better its position is, i.e., it has a larger fitness function value. Glowworms have their own dynamic line of sight, which we call the decision domain, whose range is related to the density of the neighboring nodes. If the density of neighboring nodes is low, then the decision radius of glowworms will increase. Conversely, the decision radius is reduced when the glowworms move toward the same kind of strong fluorescence in the decision domain. Reachingthe maximum number of iterations, all glowworms will be located in optimal positions.

3.1. Clustering for Load Balancing using GSO

The clustered routing scheme mainly consists of five stages: fluorescein concentration updating, neighbor set updating, decision domain radius updating, moving probability updating, and glowworm location updating. The fluoresce in concentration updating model is characterized by

$$l_i(t)=(1-\alpha)l_i(t-1)+\beta f(x_i(t)) \ \ldots (1)$$

where $l_i(t)$ represents fluorescein concentration of the i[th] glowworm at time t, α is the fluorescein volatilization coefficient, β is the fluorescein enhancement factor, f (x) is the fitness function and $x_i(t)$ is the position of glowworm i at t time. The neighbor set updating model is characterized by

$$N_i(t)=\left\{j;\left\|x_j(t)-x_i(t)\right\|<r_d^i;l_i(t)<l_j(t)\right\} \ \ldots (2)$$

where $N_i(t)$ represents the neighbor set of the i[th] glowworm at time t and $r_d^i(t)$ indicates the radius of the decision domain of the i[th] glowworm at moment t . The decision domain radius updating model is defined as

$$r_d^i(t+1)=\min\left\{rs,\max\left\{r_d^i(t)+\gamma(n_i-|n_i(t)|)\right\}\right\} \ \ldots (3)$$

where r_s is the perceived radius of glowworm, γ represents the rate of change of the decision domain, and n_i is the neighbor threshold. The moving probability of the updated model is shown in

$$P_{ij}(t)=\frac{l_j(t)-l_i(t)}{\sum_{k\in N_t}l_k(t)-l_i(t)} \ \ldots (4)$$

where $P_{ij}(t)$ indicates the probability that the glowworm i moves to the glowworm j at t time. The glowworm position updating model is expressed as

$$x_i(t+1)=x_i(t)+s\left(\frac{x_j(t)-x_i(t)}{\left\|x_j(t)-x_i(t)\right\|}\right) \ldots (5)$$

The GSO fitness function is capable enough to perform clustering operation in MANETs. Because the clustering algorithm is generally complex, a large amount of control information needs to be exchanged between nodes in the process of cluster head selection, which will bring some overhead. Consequently, this paper proposes a GSO fitness function. The GSO fitness function takes into account the local density of each cluster head, the average distance within cluster, the energy consumption of nodes within a cluster and the dispersibility of the cluster head. These parameters can reasonably control the generation of uneven network clustering. When choosingcluster head, try to disperse cluster head, avoid missing data information, make the nearest node to join cluster head quickly, and the energy consumption of cluster head is much greater than that of other member nodes. Cluster head energy is also evaluated to analyze the effectiveness. The cluster head is always served by the node with the highest energy. This can effectively balance the energy consumption of cluster heads. The key node in the network is cluster heads.

For that reason, the location of cluster heads is planned in order to minimize the size of cluster heads close to the sink nodes, so that multiple cluster heads can undertake data forwarding tasks and improve the real-time performance and energy consumption of cluster heads. When using the GSO fitness function to solve for the optimal clustering method, the design of the fitness function must consider the local density of the cluster head, the average distance within the cluster and the energy dissipation of the nodes in the cluster. It must also reasonably control the uneven network clustering caused by the dispersion of cluster heads.

At first, the base station calculates the average energy of all nodes based on the energy information from the network node. A node whose residual energy is larger than the average energy is considered as a candidate cluster head of the current round. Then, the source mobile node runs the GSO algorithm to determine the optimal clustering method or find a maximum fitness value via the fitness function shown in

$$f(x)=\varepsilon_1 f_1(p_j)+\varepsilon_2 f_2(p_j)+\varepsilon_3 f_3(p_j)+\varepsilon_4 f_4(p_j) \ldots (6)$$

The local density ρ_i of the cluster head is constructed from a kernel function as expressed in

$$\rho_i=\sum_{j\in I_s}e^{-\left(\frac{d_{ij}}{d_c}\right)^2} \ \ldots (7)$$

where $S=\{a_i\}_{i-1}^k$ denotes the cluster head, d_c is the truncation distance, and $d(a_i,a_j)$ denotes the distance between cluster head a_i and cluster head a_j. f_1 is the cluster head adjacent distance evaluation factor. If the adjacent distance is large, the cluster heads with and without large local densities are more dispersed. The dispersion of the cluster heads can be achieved by restricting the adjacent distance of the cluster head. The term f_1 is defined by

$$f_1=\begin{cases}\min\limits_{j\in I_S^i}\{d_{ij}\},I_S^i\neq\phi\\ \max\limits_{j\in I_S^i}\{d_{ij}\},I_S^i\neq\phi\end{cases} \ldots (8)$$

$$I_S^i=\{k\in I_s:f_k>f_i\} \ldots (9)$$

where f_2 is the cluster compactness evaluation factor and the minimum average distance between the node and cluster head can be determined using

$$f_2=\frac{1}{\max_{K=1,2,\ldots K}\left\{\sum\forall n_i\in C_{P_j,k}\ \frac{d\left(n_i,CH_{P_j,K}\right)}{\left|C_{P_j,K}\right|}\right\}} \ldots (10)$$

where $d\left(n_i,CH_{P_j,K}\right)$ represents the distance between node n i andthe corresponding cluster head, and $\left|C_{P_j,K}\right|$ denotes the number ofnodes in the cluster C_K. f_3 is the cluster head energy evaluationfactor and the ratio of cluster head energy to energy sum of allnodes in the network is found by using,

$$f_3 = \frac{\sum_{K=1}^{K} E(CH_{P_j,K})}{\sum_{i=1}^{N} E(n_i)} \ldots (11)$$

f_4 is the cluster head position evaluation factor, NC is thenetwork center, and the cluster head position can be determinedby,

$$f_4 = \frac{K\ X\ d(BS, NC)}{\sum_{i=1}^{K} d(BS, CH_{P_j,k})} \ldots (12)$$

The weight coefficient of each evaluation factor satisfiesε 1 + ε 2 + ε 3 + ε 4 = 1. According to the design of the fitness function,the maximum fitness function value can satisfy the following: thecluster head dispersion is better, the cluster geometry is compact,the cluster head energy is larger, and the cluster head is closerto the base station. The cluster formed by the fitness functioncan consume less energy and have more scattered cluster heads;thus, smaller clusters are formed in the vicinity of the base station,which effectively balances the energy dissipation between theclusters.

3.2. Routing mechanism

In EA-AOMDV protocol, the communication starts whensource node tries to send a packet to the destination, it checks itsrouting table for a route to the destination. If an effective routeis available, source node uses this route to send packets directly;otherwise, the packet will have stored in the sending buffer and thesource start the route discovery process.Source node start the route discovery phase by broadcasting Route REQuest (RREQ) packet to all nodes within its wirelessrange. We added two additional fields to the RREQ packet tocontain the path residual energy (PRE) and minimum hopenergy (MHE) as shown in Fig. (2). The source node inserts the value of its residual energy in the PRE field and sets the value ofMHE field to Zero in the RREQ packet before broadcasting it.When the RREQ packet reaches intermediate nodes, thispacket is dropped if it has been received before to preventrouting loops. If it was not received before, the broadcast id isremembered to prevent receiving the same packet twice. Theintermediate node compares its residual energy with the value ofMHE field in the RREQ packet and the value of MHE field willbe updated. Then the intermediate node adds the value of its residualenergy to the value of PRE field in the RREQ packet. The valueof PRE field will be updated. Based on the value of PRE and MHE, the intermediate nodecalculates the energy metric of the corresponding path and establish or update reverse path from this node to thesource node.

IV. SIMULATION SETTINGS AND PERFORMANCE METRICS

200 mobile nodes are deployed over 2000 X 2000 meters' terrain space. IEEE 802.11 MAC standard is employed with the bandwidth of 1 Mb/s and the packet size is fixed to 512 bytes that transmit in constant bit rate fashion. Each node is allowed to move freely over the terrain space with random waypoint model and the speed of the mobile nodes are varied from 10 m/s to 30 m/s with standard initial energy of all the nodes set to 2. joules. The simulation settings are presented in Table – 1.

Performance metrics namely packet delivery ratio, throughput, packets drop, overhead and delay are taken for evaluating the efficiency of the GSO-COD-LBS over other load balancing protocols.

Table – 1. Simulation settings

Parameter	Value
Standard	IEEE 802.11 standard
Area size	2000 m X 2000 m
Packet size	512 bytes
Traffic type	Constant Bit Rate
Transmission range	250 m
Number of nodes	200
Simulation time	5000 seconds
Speed	10, 15, 20, 25, 30 m/s
Initial Energy	2.5 joules
Bandwidth	1 Mb/s
Mobility type	Random waypoint model

V. RESULTS AND DISCUSSIONS

Performance analysis in terms of packet delivery ratio by varying the mobility speed ranging from 10 m/s to 30 m/s and the results are presented in table 2. GSO-COD-LBS performs better when compared with the existing routing solutions and also outperforms our earlier works [16] – [18]. The packet delivery ratio ranges at the maximum of 0.98 (approximately 98%) when the mobile nodes are moving around at the speed of 10 m/s and at the minimum of 0.96 (approximately 96%). The results are projected in the Fig.1.

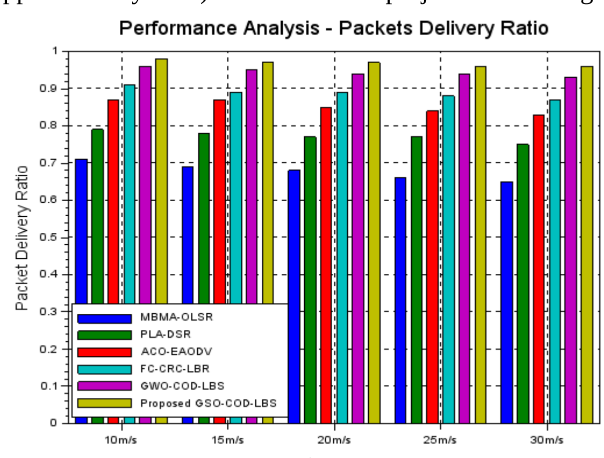

Fig. 1. Performance Analysis – Packet Delivery Ratio

Table – 2. Performance Analysis – Packet Delivery Ratio

	MBMA-OLSR [14]	PLA-DSR [15]	ACO-EAODV [16]	FC-CRC-LBR [17]	GWO-COD-LBS [18]	Proposed GSO-COD-LBS
10 m/s	0.71	0.79	0.87	0.91	0.96	0.98
15 m/s	0.69	0.78	0.87	0.89	0.95	0.97
20 m/s	0.68	0.77	0.85	0.89	0.94	0.97
25 m/s	0.66	0.77	0.84	0.88	0.94	0.96
30 m/s	0.65	0.75	0.83	0.87	0.93	0.96

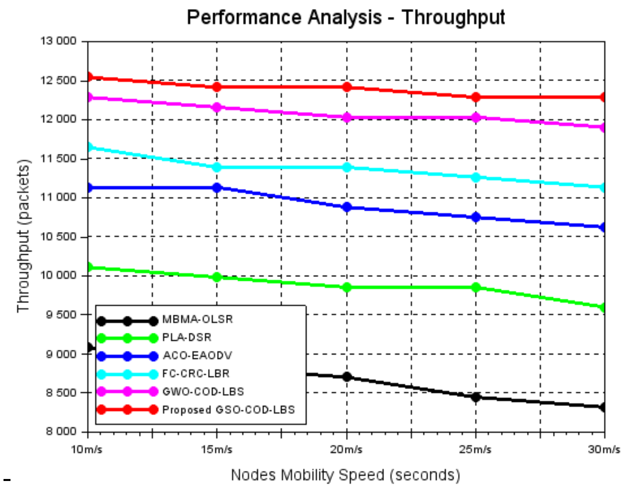

Fig. 2. Performance Analysis – Throughput

Table – 3. Performance Analysis – Throughput

	MBMA-OLSR [14]	PLA-DSR [15]	ACO-EAODV [16]	FC-CRC-LBR [17]	GWO-COD-LBS [18]	Proposed GSO-COD-LBS
10 m/s	9088	10112	11136	11648	12288	12544
15 m/s	8832	9984	11136	11392	12160	12416
20 m/s	8704	9856	10880	11392	12032	12416
25 m/s	8448	9856	10752	11264	12032	12288
30 m/s	8320	9600	10624	11136	11904	12288

Performance analysis in terms of throughput whilst the nodes are moving around the terrain range with the mobility speed ranging from 10 m/s to 30 m/s and the results are presented in table 3. It is clear from the simulation results that GSO-COD-LBS performs better when compared with the other works. Throughput ranges at the maximum of 12544 packets when the mobile nodes are moving around at the speed of 10 m/s and at the minimum of 12288 packets when the mobility speed of the nodes increases to 30 m/s and the graphical outcome is depicted in Fig. 2.

Performance analysis in terms of packet drop as the nodes are moving around the terrain range with the mobility speed ranging from 10 m/s to 30 m/s is showcased in table 4. The obtained results present that GSO-COD-LBS performs all the existing and the earlier proposed routing solutions. Packets drop falls at the maximum of 512 packets when the mobile nodes are moving around at the speed of 30 m/s and at the minimum of 256 packets when the mobile nodes are moving around the speed of 10 m/s. The output is presented in Fig. 3.

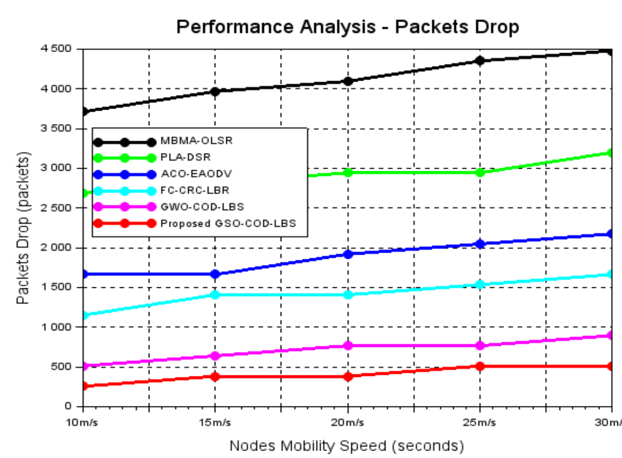

Fig.3. Performance Analysis – Packets Drop

Table – 4. Performance Analysis – Packets Drop

	MBMA-OLSR [14]	PLA-DSR [15]	ACO-EAODV [16]	FC-CRC-LBR [17]	GWO-COD-LBS [18]	Proposed GSO-COD-LBS
10 m/s	3712	2688	1664	1152	512	256
15 m/s	3968	2816	1664	1408	640	384
20 m/s	4096	2944	1920	1408	768	384
25 m/s	4352	2944	2048	1536	768	512
30 m/s	4480	3200	2176	1664	896	512

Table – 5. Performance Analysis – Packets Overhead

	MBMA-OLSR [14]	PLA-DSR [15]	ACO-EAODV [16]	FC-CRC-LBR [17]	GWO-COD-LBS [18]	Proposed GSO-COD-LBS
10 m/s	389	296	267	190	109	57
15 m/s	416	319	275	193	132	64
20 m/s	479	324	275	217	132	73
25 m/s	487	343	282	244	132	85
30 m/s	499	380	295	266	148	98

Table – 6. Performance Analysis – Delay

	MBMA-OLSR [14]	PLA-DSR [15]	ACO-EAODV [16]	FC-CRC-LBR [17]	GWO-COD-LBS [18]	Proposed GSO-COD-LBS
10 m/s	454.40	424.70	400.90	291.20	184.32	108.97
15 m/s	415.10	419.33	322.94	284.80	218.88	137.89
20 m/s	435.20	394.24	315.52	193.66	204.54	132.95
25 m/s	422.40	433.66	322.56	247.81	216.58	147.27
30 m/s	391.04	432.00	329.34	267.26	202.37	143.68

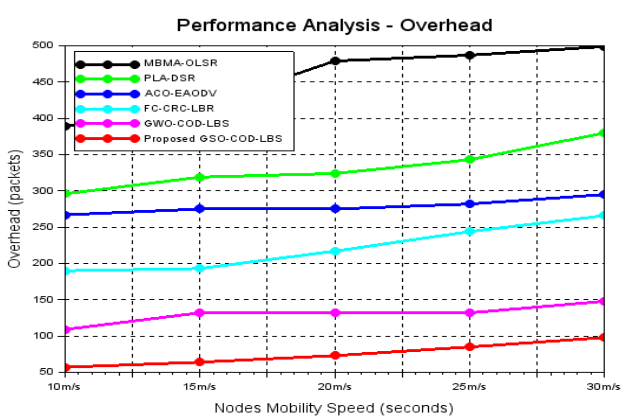

Fig. 4. Performance Analysis – Packets Overhead

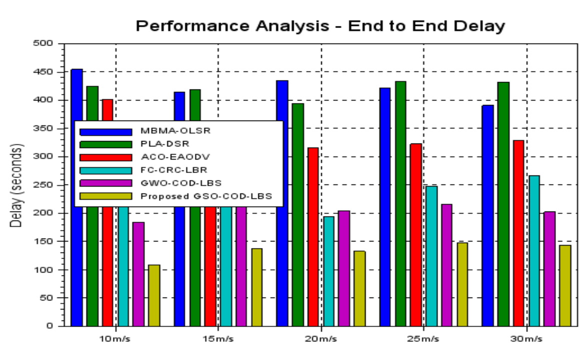

Fig. 5. Performance Analysis – End to End Delay

Performance analysis in terms of overhead as the nodes are moving around the terrain range with the mobility speed ranging from 10 m/s to 30 m/s is presented in table 5. It is inferred that GSO-COD-LBS outperforms than that of existing works and our earlier proposed load balanced routing schemes. The number of overhead packets reaches at the maximum of 98 packets when the mobile nodes are moving around at the speed of 30 m/s and at the minimum of 57 packets when the mobile nodes are moving around the speed of 10 m/s. The graphical outcome of the simulation is shown in Fig. 4.

Performance analysis in terms of delay as the mobile nodes are at the terrain range with the mobility speed from 10 m/s to 30 m/s is given in table 6. From the obtained simulation results it is inferred that when the mobility speed of nodes increases over the terrain region, the delay in transmission is also increases and at the same time the proposed GSO-COD-LBS is comparatively performs better than that of other routing schemes / protocols and the results are shown in Fig. 5.

VI. CONCLUSION

In this part of research work, GSO is employed for clustering. Energy aware routing with load balancing scheme is presented for ensuring QoS in MANETs. The fitness function that best suits for MANET is formulated that helps the GSO to perform the clustering operation. An adaptive routing mechanism that works in on – demand fashion is also employed for transmitting packets from source mobile node to destination mobile node. Simulations are performed and from the performance results it is ensured that GSO-COD-LBS outperforms other existing routing protocols and our earlier published works.

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