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Grey Wolf Optimization based Clustered on – Demand Load Balancing Scheme (GWO-COD-LBS) for Heterogeneous Mobile Ad hoc Networks

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Abstract- Load balancing is the research dimension in the field of mobile ad hoc networks. From the several previously conducted research works it is inferred that clustering based load balancing approach offers better solution. Many protocols are proposed formerly, and multipath routing seems to be better one. This research work aims to make use of grey wolf optimization technique for clustering the nodes. Conventional multipath routing strategy is employed along with adaptive load balancing approach. Simulation settings are made and the performance metrics namely packet delivery ratio, throughput, packets drop, overhead and delay are taken into account for evaluating the efficiency of the approach.

Keywords: MANET, load balancing, clustering, grey wolf optimization, packet delivery ratio, throughput, delay.

I. INTRODUCTION

Mobile Ad hoc Network (MANET) is recognized and investigated as the untainteduniversal purpose networking architype of multi-hop ad hocnetworks. Wide-rangingtenacity denotes that these networks are designed without any specific applications in mind, butrather to support any legacy TCP/IP applications. In MANETs, people with smart devices (mobilenodes) which are battery-powered can freely and dynamically form a self-configuring MANET to send, receive and sharedata in a restricted terrain region. Henceforward, the wireless connection between the mobile nodes and the topology of the network will changefrequently. There is a variety of applications for MANET paradigm, especially in places where there are difficulties in thedeployment of network infrastructures such as in battlefield communications, disaster recovery, crisis management services and health care. The limited battery capacity and the mobility of nodes are key features in MANETs which render routing in such mobile environments a challenging issue. In MANETs, load balancingare becoming more serious than common network failures. Furthermore, the changes of topology due to the mobility of nodes also affect the consumed energy for data transmission. Therefore, routing schemes in MANETs need to comprise mechanisms that cope with the challenges incurred by the mobility of nodes, the changes of topology and the limitations of energy resources. Additionally, the routing protocols should be efficient in terms of the quality of service (QoS) and network load to be balanced and ensure data transmission over the wireless channel. This research work aims in design and development of Grey Wolf Optimization based Clustered On – Demand Load Balancing Scheme for heterogeneous MANETs.

1.1. Motivation

MANET falls into the kind of decentralized infrastructure-less networks that operate based on a self-organizing paradigm. At a point of time when a set of mobile nodes, equipped with wireless interfaces dynamically connect with one another in an infrastructure-less manner, an ad hoc network is formed. Ad hoc networks do not rely on a fixed infrastructure, which makes them ideal for many applications such as emergency services and tactical/military operations. In MANET, nodes communicate using wireless interfaces via the communication medium (using spectrum/channels). One of the well-known communication standards that support infrastructure-less mode of operation is IEEE 802.11. Due to the nature of wireless communication and limitations of currently deployed MAC (medium access control) protocols, the challenges involved with ad hoc networks are significantly more than infrastructure-based wireless networks. This research work chooses the load balancing problem in MANET.

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 GWO-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 immigrants 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 multimetric clustering problem.

Shengxiang 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

The proposed work contains three phases namely grey wolf optimization based clustering, on – demand multipath routing and adaptive load balancing.

3.1. Grey wolf optimization based clustering

In this research work, clustering mechanism is carried out using the social behaviour of grey wolves. Firstly, thedata is obtained by the parameters namely number of nodes, transmission range and size of the grid. Then,the mobile ad hoc network is deployed over the grid. Certain number of features such as node's mobility speed, direction, locationinformation are also taken into account for performing the clustering operation. It is made mandatory that a mobile node is supposed to be in one cluster. At the same time, the mobile nodes are not allowed to be amember of more than one cluster. In every cluster there is a cluster head mobile node CH and it will administer the entire cluster and also the member mobile nodes. It is to be noted that, CH node keeps tracks of new mobile nodes and the mobile nodes that are leaving out of the clusters. Grey wolfare habitually in a group of five to twelve members.The grey wolf begins from alpha (α) type. α (alpha) type grey wolves is the leader and it instructs the other wolves. Other type of wolves follows the instructions. Certain decisions of whole carton are usually taken by the alpha wolves such as sleeping,wakeup time and many mores. After the alpha wolf, next comes beta (β) grey wolves. Beta type grey wolves areconsidered as second in the hierarchy and they support the alpha wolves for making the decision and betashelp the alphas for implementation of their instruction to the lower level of grey wolves among others. Beta wolves are usedby the alphas for the feedback purpose as well. If any of the alpha wolves die, then one of the betas wolf is promoted toalpha wolf. Third level of grey wolves are Delta (δ) wolves. These wolves are categorized into spies, guards, predators and caretakers.Delta wolves help to protect the complete pack, also they keep eyes on the boundaries so that in case of danger countermeasures can be taken for the pack. Hunters (Delta) provide the food for the others, caretakers look after the aged, weakand sick wolves in the pack. If case of death of beta wolf the senior delta wolf is promoted to beta wolf.The four steps carried out by grey wolf optimization begins from exploration (searching) to exploitation (attacking).Omega type of wolves are placed in the last position among grey wolf's hierarchy. Due to the last in the position of wolves Omega type wolves always have to pay more thanothers in return of very small reward. Death of delta promotes theany one of the omega to delta. There are some important phases of the grey wolf for the hunting as portrayed in the forthcoming readings.

3.1.1. Social hierarchy

Alpha (α) is considered as the fittest solution in the ordering of grey wolf optimization. Beta (β) is considered as thesecond most and consequently delta (δ) and omega (ω). α, β, δ is used for the guidance for the hunting purpose. Omega (ω) wolves just follow all three of upper hierarchy.

3.1.2. Prey encircling

Grey wolf encircle the prey during the process of hunting as;

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - X(t)\right| \ldots (1)$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \ldots (2)$$

where A and C are co-efficient vectors, X_P is the position vector of prey, X is the position vector of grey wolves. The vector $\vec{A}$ and $\vec{C}$; $\vec{D}$ is the two dimensional position of the possible neighbours.

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \ldots (3)$$

$$\vec{C} = 2.\vec{r_2} \ldots (4)$$

In the above equations (3) and (4), $\vec{r_1}$ and $\vec{r_2}$ are random vector range from 0 to 1. $\vec{a}$ is the factor which linearly decrease from2 to 0. Eqs. (1) and (2) is used to update the position of wolves from current location to new-location.If wolf is at position (X, Y) andprey at (X^*, Y^*). The grey wolf will update its position according to the movement of prey which is mathematically modelledas in Eqs. (3) and (4). The positions are adjusted with the help of vectors $\vec{A}$ and $\vec{C}$. if the wolf is at any position (X, Y, Z) and prey at (X^*, Y^*,Z^*) any of the position in 3-D so wolf will update their new position of random vectors $\vec{r_1}$ *and* $\vec{r_2}$.

3.1.3. Hunting the prey

These wolves try to find the location of optimum (prey) and encircle it for the hunting. Alpha are the senior most ormost strengthen wolves in the whole pack designates for the hunting. Sometime betas and deltas also perform this (hunting)task. In mathematical stimulation we store the best three solutions and convey it to remaining wolves (Omega) for updatingtheir position accordingly. These tasks are performed with the help of following equations

$$\vec{D_\alpha} = \left|\vec{C_1}.\vec{X_\alpha} - \vec{X}\right| \ldots (5)$$

$$\vec{D_\beta} = \left|\vec{C_1}.\vec{X_\beta} - \vec{X}\right| \ldots (6)$$

$$\vec{D_\delta} = \left|\vec{C_1}.\vec{X_\delta} - \vec{X}\right| \ldots (7)$$

$$\vec{X_1} = \vec{X_\alpha} - \vec{A_1}.(\vec{D_\alpha}) \ldots (8)$$

$$\vec{X_2} = \vec{X_\beta} - \vec{A_2}.(\vec{D_\beta}) \ldots (9)$$

$$\vec{X_3} = \vec{X_\delta} - \vec{A_3}.(\vec{D_\delta}) \ldots (10)$$

$$\vec{X}(t+1) = \frac{\vec{X_1} + \vec{X_2} + \vec{X_3}}{3} \ldots (11)$$

3.1.4. Exploitation

After encircling and harassing the prey, grey wolves attacks the prey when it stops moving. We modelled it in mathematicalequations by taking the value of $\vec{\alpha}$. if the value of | A | <1, it enforces the wolf pack to attack the optimum (prey). Moreover, if value of | A | >1, thisenforces grey wolves to explore more area instead of exploitation.

$$a = 2 - 1 * \left[\frac{2}{Max_{iter}} \right] \ldots (12)$$

3.1.5. Overall Clustering Operation using Grey Wolf Optimization

At first, the position of the mobile nodes gets initiated randomly on the deployed terrain space. The mobile nodes are also initialized with certain amount of speed.The solution-set is generated over the search space. Then, the fitness of Grey wolf is obtained to create cluster. The fitness is calculated based on the maximum remaining energy of the mobile nodes. Afterevery iteration the position of the mobile nodes is updated and new fitness values are obtained in order to find the optimized results. Thealpha wolf contains the minimum value as it is considered the best solution, followed by beta and delta respectively. Lastly,the alpha gives us the optimize number of clusters.The value $\vec{a}$ is very important as it is the linearly decreasing factor. When the value of a reaches to zero it give us theoptimize solution. The nodes are initialized in thenetwork randomly, the cluster matrix is created by finding the neighbours and keeping in mind that only one node is chosen as the member in the corresponding cluster. Furthermore, the two objective variable $W_1$and W_2 is used to evaluate the cluster matrix. Thecondition of maximum iteration, which is also the stopping criteria is used. In the next stage the fitness values of searchagents (maximum remaining energy) are calculated. The linearly decreasing factor is also used to take the execution toward the result. After single iterationthe positions of nodes are updated and process continues. At the end, then linearly decreasing factor a moves toward zero,the alpha wolf gives us the optimized solution. The number of clusters in this case.Searching the prey or exploration is the main task performed by the grey wolf which is dependent on the position ofalpha, beta and delta. These wolves spread in the search space for the exploration and then converge to attack the hunt. $\vec{A}$, values greater than 1 or less than −1 help the grey wolves to move away from the hunt. Due towhich it enforce the search agents to explore globally. As mentioned earlier that $|A| > 1$ means search for the better prey.Vector $\vec{C}$ also has range from [0, 2]. If the value of C <1 it deemphasizes and if $C > 1$ it emphasizes prey in defining thedistance. The vector $\vec{C}$ helps the optimizer to avoid the local optima and enforce the process of exploration. It is significant tosay here that $\vec{C}$ is not linearly reduced according to $\vec{A}$. The value of $\vec{C}$ is assigned intentionally so that it favors the searchingof search space in all the iterations (from initial to final) to track the fitter prey. Because there is a possibility that may befitter solution can be found in final iteration. $\vec{C}$ is also known as the effect of obstacles in the path for finding the prey.Basically these obstacles in the path of approaching forces to search thoroughly and stop from rapidly and handily findingprey. $\vec{C}$ actually assigns some random weight to the prey so that it will become hard to find by the wolves. The valueof *a_* also decreases from 2 to 0 so that wolves can be force to attack the prey (exploit) or search the prey for fitter solution(explore). $\vec{A}$ also enforces to converge or diverge from prey. At last, this process terminated byend criterion. In this research work, the maximum number of iteration is set to 100 (which can further be increased in further works).

3.2. On – demand multipath routing

In the proposed routing scheme route request(RREQ) propagation from the source towards the destination establishes multiple reverse paths both at intermediate nodes as well as the destination. Multiple route replies(RREPs) traverse these reverse paths back to form multiple forward paths to the destination at the source and intermediate nodes.This proposed work adopts several feature of conventional AOMDV protocol namely the set of multiple paths that are loop-free and the alternate paths at every node that are disjoint. Also, low inter-nodal coordination overheads, ability to discover disjoint paths without using source routing, minimal additional overhead over AODV to obtain alternate paths are also incorporated in this research work.

3.3. Adaptive load balancing

The GWO-COD-LBS enhances the obtained multiple paths. To balance the load on the wireless links, a local hash table is assigned along with airtime metric. A downlink with minimal airtime metric will be included in the number of discovered paths. The load index (LI)metric is used to measure the loads on links. The LI is assignedbased on the background load on-demand for the outgoing link.Links with a load greater than two-thirds of the total availablecapacity of the band are allotted a load index of 1. Hence, if thecapacity of the band is C, then the load threshold value is given by

$$B = \frac{2 \times C}{3} \ldots (13)$$

The subsequent load indices are assigned a decrease of 0.5 timesthan the previous load threshold value. Thus, the links with loadindices of 2, 3 and 4 contain a load greater than $\frac{C}{3}, \frac{C}{6}, \frac{C}{12}$ respectively.To evaluate the degree of load balancing, the LI is set to a fairness index among the loads in the sub-indices thatare the links in a path, as in Eq. (14).

$$L(I) = \frac{\sum f_{x_i}}{k \sum f_{x_i}^2} \ldots (14)$$

where k is the number of links in the path I, L is the aggregated loadindex of the path, and f_{x_i} is the load for sub index i. The load of eachlink is balanced with reference to the hash table of the load indicesof all neighbouring links. All the subsequent overloaded links in Iare balanced by replacing them with an alternate low-demand linkuntil the entire flow is load balanced.

IV. SIMULATION SETTINGS AND PERFORMANCE METRICS

200 mobile nodes are deployed over 2000 X 2000 meter 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 GWO-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

Table – 2 showcases performance analysis in terms of packet delivery ratio by varying the mobility speed ranging from 10 m/s to 30 m/s. From the results it is inferred that GWO-COD-LBS performs better when compared with the other works. The packet delivery ratio ranges at the maximum of 0.96 (approximately 96%) when the mobile nodes are moving around at the speed of 10 m/s and at the minimum of 0.93 (approximately 93%). The results are projected in the Fig.1. The output is shown as picture in Fig. 1.

Table – 3presents performance analysis in terms of throughputwhilst the nodes are moving around the terrain range with the mobility speed ranging from 10 m/s to 30 m/s. From the results it is clear that GWO-COD-LBS performs better when compared with the other works. Throughput ranges at the maximum of 12288 packets when the mobile nodes are moving around at the speed of 10 m/s and at the minimum of 11904 packets. The graphical result is shown in Fig. 2.

Table – 4 presents 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. From the results it is inferred that GWO-COD-LBS outperforms compared with the other existing works. Packets drop falls at the maximum of 896 packets when the mobile nodes are moving around at the speed of 30 m/s and at the minimum of 512 packets when the mobile nodes are moving around the speed of 10 m/s. The output is shown in Fig. 3.

Table – 5 portrays the 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. From the results it is observed that GWO-COD-LBS performs than that of existing works. The number of overhead packets reaches at the maximum of 109 packets when the mobile nodes are moving around at the speed of 30 m/s and at the minimum of 148 packets when the mobile nodes are moving around the speed of 10 m/s. The graphical representation is portrayed in Fig. 4.

Table – 6 projects the 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. It is evident that when the mobility speed of nodes increases over the terrain region, the delay in transmission is also increases. It is noteworthy that GWO-COD-LBS is consistently performs better than that of other routing schemes / protocols. The results are portrayed in Fig. 5.

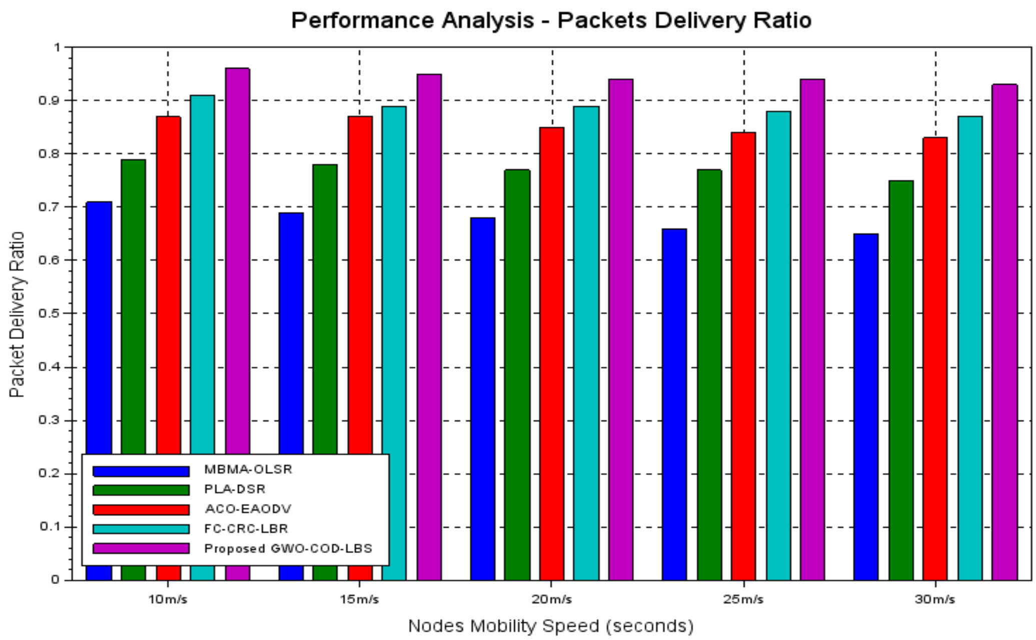

Fig. 1. Performance Analysis – Packet Delivery Ratio

Table – 2. Performance Analysis – Packet Delivery Ratio

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

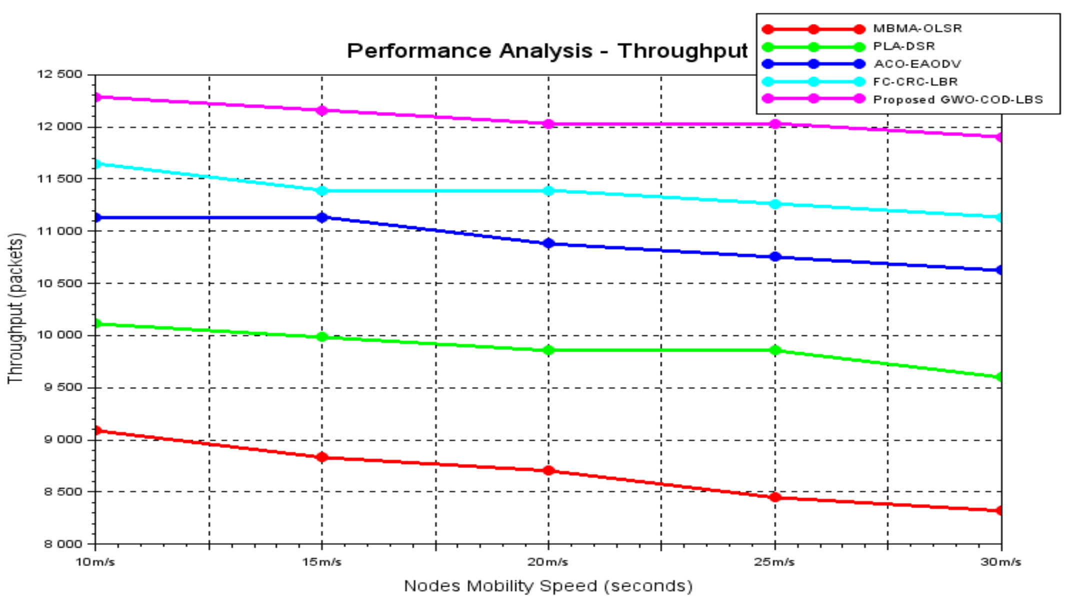

Fig. 2. Performance Analysis – Throughput

Table – 3. Performance Analysis – Throughput

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

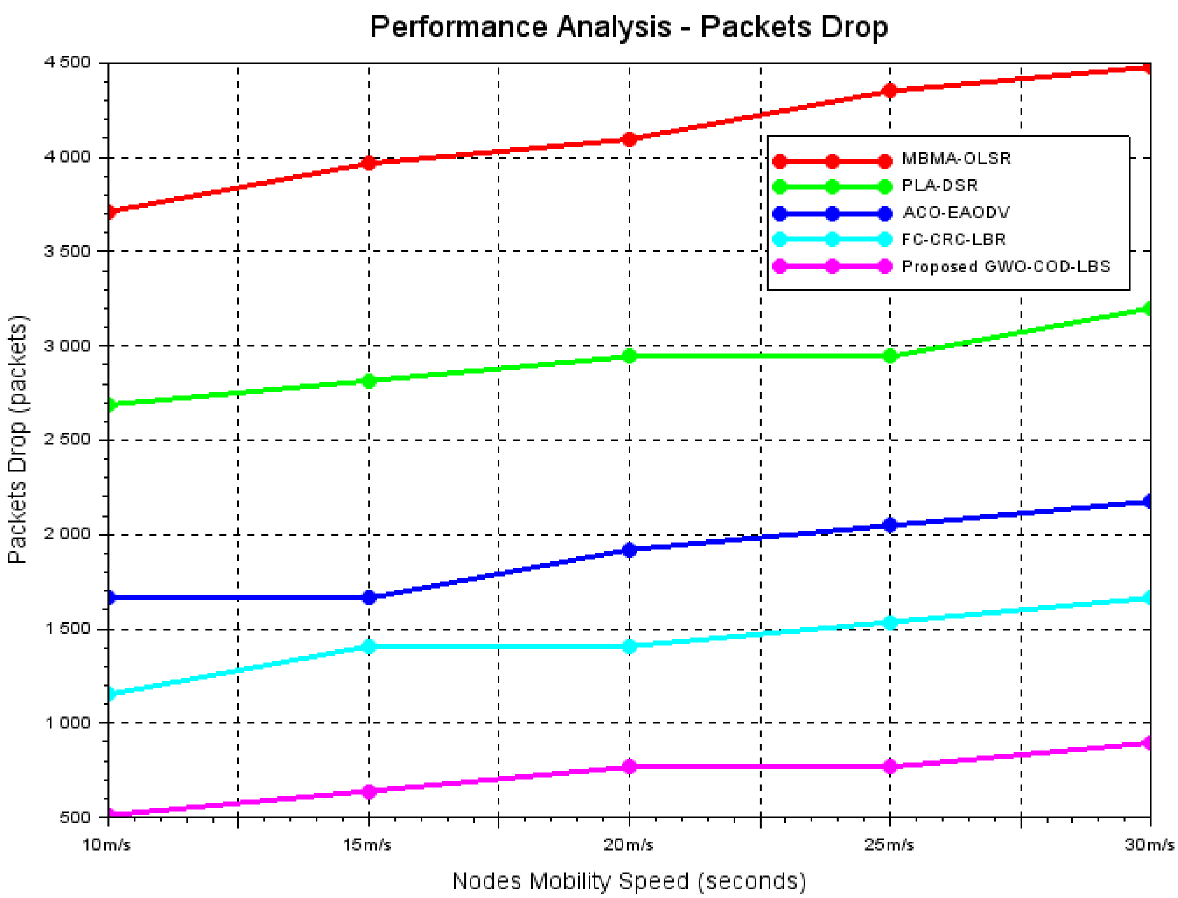

Fig. 3. Performance Analysis – Packets Drop

Table – 4. Performance Analysis – Packets Drop

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

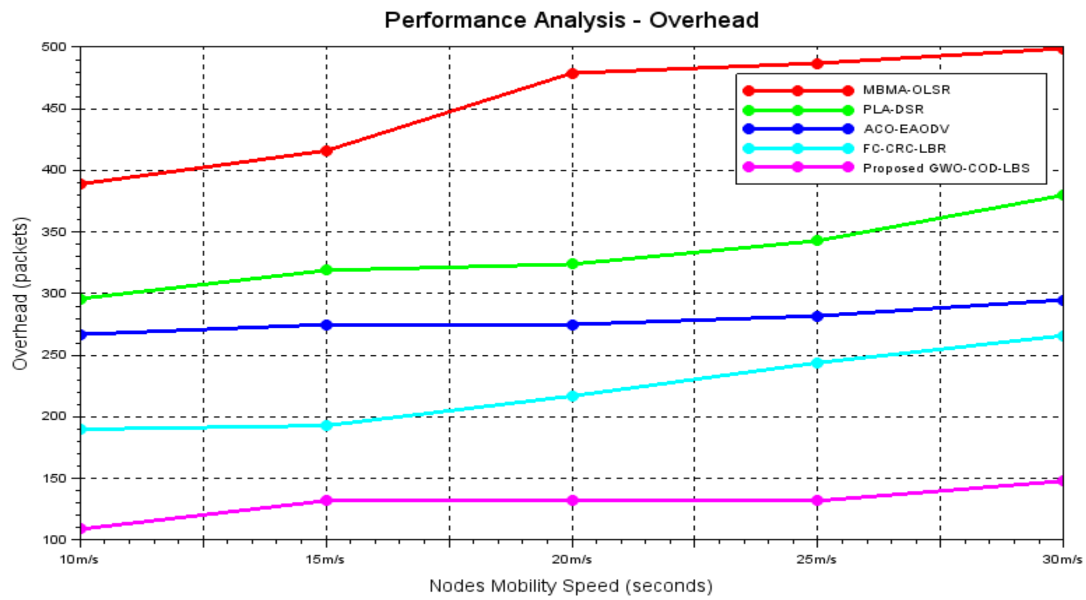

Fig. 4. Performance Analysis – Overhead

Table – 5. Performance Analysis – Overhead

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

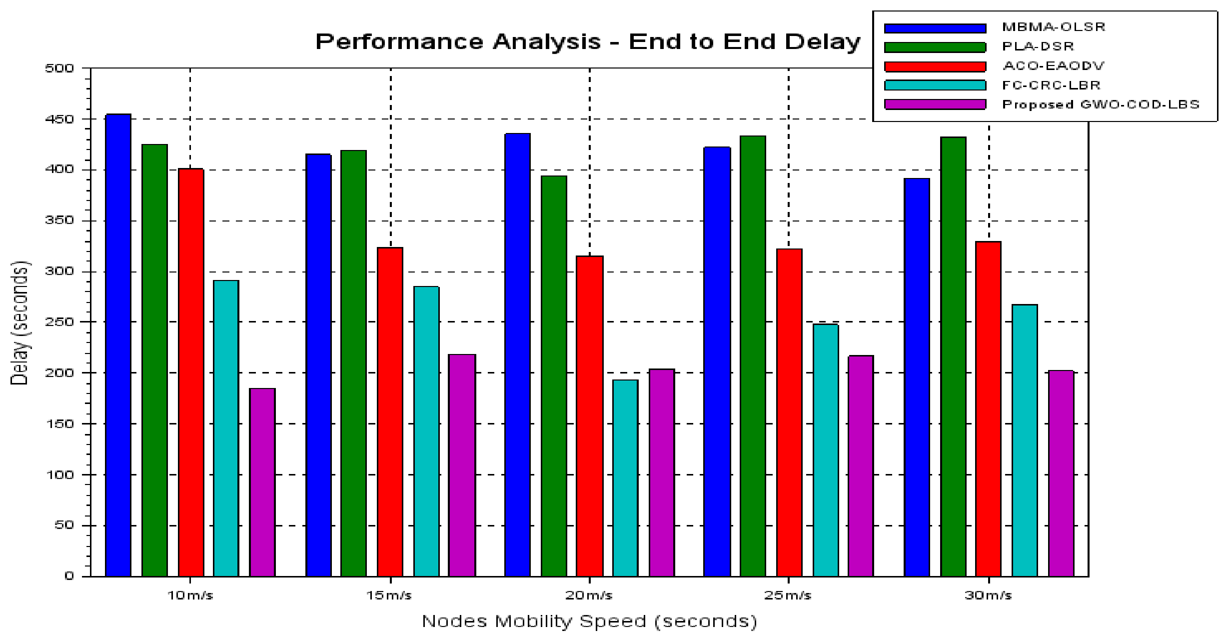

Fig. 5. Performance Analysis – Delay

Table – 6. Performance Analysis – Delay

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

VI. CONCLUSION

This is the extension of our previous research works that can be found in the literatures [16] – [17]. The grey wolf optimization (GWO) algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature that closely relates with this research work. In this research clustering operation is performed by making use of grey wolf optimization algorithm. The choice of GWO employed in this research work is due to the adaptive nature of optimization. Multiple paths are discovered in on-demand fashion. Adaptive load balancing approach is employed by deriving out load index metric. Simulation results are promising in terms of obtained performance metrics namely packet delivery ratio, throughput, packets drop, overhead and delay.

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