An Energy Efficient Clustering Based Grey Wolf Optimization For Mobile Ad-Hoc Network

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Abstract- *In recent days, Mobile Ad hoc Network (MANET) become ubiquitous and find helpful in various scenario. Due to the inadequate battery power of mobile nodes the overall network system gets affected. Exploitation of energy is look upon as a major parameter. Hence energy efficient routing protocol in MANET become obligatory. This project discusses the energy efficient population based application of Grey Wolf Optimization (GWO) algorithm for the minimization of energy consumption using Ad hoc On demand +Multipath Distance Vector routing (AOMDV) protocol. The optimal routes between two mobile nodes is determined by the fitness function (FF) to diminish the utilization of energy in multipath routing. The presented FF-AOMDV model is simulated using Network Simulator 2 (NS-2) and a complete evaluation is made in PSO algorithm under several measures.*

Keywords- MANET, Grey Wolf Optimization, Routing Protocol, Fitness Function.

I. INTRODUCTION

Mobile ad hoc Network also termed as wireless ad hoc network that frequently have a routable networking environment on the top of a Link Layer ad hoc network. The mobile nodes are connected wirelessly in a self configured, self curing network without having a central administration. Hence MANET is also called as infrastructure less network. In MANET, the batteries of the mobile nodes exhausted very quickly due to the frequent changes of topology which decrease the network performance. Hence energy consumption is considered as the critical issue as most mobile nodes run on inadequate battery resources. Routing is a most important component of any system and accountable for several operations between source and destination nodes to enhance the reliability of data transmission. The three major routing Protocols in MANET are discussed below.

1.1. Proactive routing protocol or table driven approach

This routing protocol maintains regular and up to date routing information about each and every path by spreading route updating scheme at fixed time intervals. Example of proactive routing protocols is Destination Sequenced Distance Vector Routing (DSDV), Optimized Link State Routing (OLSR) and Wireless Routing Protocol (WRP).

1.2. Reactive routing protocol or on demand driven protocol

This routing protocol establishes the route for transmission only when there is a demand. Ad Hoc On-Demand Distance Vector (AODV), Dynamic Source Routing (DSR) and Associativity Based Routing (ABR) are the Reactive routing protocol.

1.3. Hybrid routing protocol

It is a relationship of proactive and reactive protocols. In this protocol, a route is established with the help of proactive method and uses a reactive method for flooding of different mobile nodes. Example of hybrid routing protocols are Temporary Ordered Routing Algorithm (TORA), Zone Routing Protocol (ZPR) and Order One Routing Protocol (OOPR).

1.4. Characteristics of MANET

- MANET has features of distributed operation because in MANET each node operates independently and there is no centralized server or computer to manage this network.
- In MANETs the network topology is always changing because node in ad hoc networks change their position randomly as they are free to move anywhere, therefore MANET support dynamic topology.
- MANET includes several advantages over wireless network, including ease deployment, speed of deployment, higher bandwidth and decrease dependence on a fixed infrastructure.
- Energy constrained Activities.

1.5. Advantages of MANET

MANET has the following advantages:

- The facility of service access and information access are provided by the mobile nodes regardless graphical position of the mobile nodes.
- These networks can be easily established anywhere and anytime.
- Cost of estimation is very less.
- Support is not required for the development of infrastructure.

1.6. Applications of MANET

Following are the MANETs applications:

- Police area or military battlefield: ad hoc networks can be very useful in establishing communication around the group of soldiers for the tactical operation & also for the military to take advantage of commonplace and military information headquarters.
- Commercial sector: The ad hoc form of communication is especially useful into the public safety, search and rescue applications. Medical teams require rapid and effectual communications when they rush to calamity area to treat victims, the medical teams can employ ad hoc networks such as laptops and PDAs and can communicate via the wireless link with the hospital and the medical teams on-site.
- Local level: An ad hoc network finds application in using notebook and computers to spread and share information among participants at conference, at meeting, or in classrooms.

II. LITERATURE SURVEY

WahebA.Jabbar, et al. (2017) addressed Multipath Battery and Mobility Aware routing scheme (MBMA-OL SR) based on MP-OL SRv2. The study exploits a Multi-Criteria Node Rank (MCNR) metric that comprises the remaining battery energy and the rate of nodes. In evaluation to MP-OL SRv2, MBMA-OL SR does not only considerably conserve the residual battery energy of nodes, but it also reduces the number of packets dropped and transmits a greater number of packets at a lower energy cost per packet, which results into higher energy competency. However it is not appropriate if number of mobile nodes increases.

Uddin, M, et al. (2017) proposed Ad Hoc Demand Multipath Distance Vector (AOMDV) routing protocol by applying the Fitness Function technique to optimize the energy consumption. This algorithm has performed much better than both AOMR-LM and AOMDV in throughput, packet delivery ratio and end-to-end delay. Particle Swarm Optimization (PSO) algorithm is used to find the most favorable path from the source to the destination. It is not focusing on high convergence area and has less accuracy.

R.Rajakumar, et al. (2017) presented Grey Wolf Optimization algorithm to spot the correct position of unknown nodes, so as to handle the node localization problem. The numerical computation results such as convergence rate and success rate are noted and it is compared with PSO and MBA algorithms. The results of GWO algorithm are compared with other Meta heuristics approaches and thereby it achieves better performance with respect to maximum number of localized nodes.

Farhan Aadi, et al. (2018) proposed K-Means Density clustering algorithm for selection of cluster heads. Optimal cluster heads improve the cluster life span and diminish the routing overhead. The proposed model outperforms the artificial intelligence techniques such as Ant Colony Optimization-based clustering algorithm and Grey Wolf Optimization-based clustering algorithm. It is not considering on node mobility.

Sandeep Raskar, et al. (2018) intends to develop a routing approach that solves the challenges like route establishment and route recovery. The optimal route can be estimated by adopting a generalized multi-purpose optimization algorithm named Grey Wolf Optimizer. Moreover, this paper implies Neural Network to predict the node actions in the ad hoc network. The proposed routing algorithm is compared to the existing approaches, and the significance of this method is described evidently. Although the link failure is not considered.

Rashmi Chaudhry, et al. (2018) presented an optimal power control technique based on non-cooperative algorithm to achieve the goal of optimal energy conservation of a MANET. The proposed power control game uses Signal-to-Interference-plus-Noise Ratio (SINR), residual energy of nodes as an efficient pricing function to deduce the utility of nodes which achieves the required Quality of Service (QoS) of MANET. To improve energy efficiency and get fast convergence point, “Nash equilibrium”, a Logarithmic Grey Wolf Optimization (lGWO) algorithm is used to achieve global optimum solution. But Power level at MAC layer affects transmission rate and performance of routing protocol at network layer.

S. R. Drishya, et al. (2019) proposed a Modified Energy-Efficient Stable Clustering (MEESC) algorithm in which node mobility is given more significance in weight calculation for the selection of CH. However mobility calculation models are to be incorporated in the cluster head selection process to provide perfect information about the accessibility of nodes in the network.

Muhammad Yeasir Arafat, et al. (2019) proposed three dimensional (3D) swarm intelligence based localization (SIL) algorithm based on particle swarm optimization (PSO) that exploits the particle search space in a limited boundary by using the bounding box method. Convergence time and localization precision are improved with lower computational cost. Also he proposed an energy competent swarm intelligence based clustering (SIC) algorithm based on PSO, in which the particle fitness function is exploited for inter cluster distance, intra-cluster distance, residual energy, and geographic location. It needs additional administrative module to control Cluster selection overhead.

III. PROPOSED WORK

The proposed work describes clustering based grey wolf optimization, on-demand multipath routing with the existing method of particle swarm optimization algorithm.

3.1 Particle Swarm Optimization

The PSO algorithm is implemented with a population of arbitrary candidate solutions also termed as particles. Every particle solutions have a random velocity and iteratively travel through the problem space. It is fascinated towards the position of the best fitness achieved so far by the particle itself and by the location of the best fitness achieved so far across the whole population. The PSO algorithm includes some regulation parameters that deeply manipulate the algorithm performance, often declared as the exploration exploitation trade-off. Exploration is the capability to test different regions in the problem space in order to set a good optimum, confidently the universal one. Exploitation is the capability to focus the search around a hopeful candidate solution in order to locate the most favorable accurately. In this method, the solutions particles are concerned towards two fitness parameters. One is energy level of the mobile nodes and the other is distance of the route. By these two parameters, the optimization could be found by forwarding traffic through the route that has the highest level of energy and less distance in order to diminish the energy consumption related studies.

3.2 AOMDV Routing Protocol

Multipath routing is the routing method of using numerous substitute path through a network, which can give way a variety of profit such as error tolerance, enlarged bandwidth or enhanced security. This proposed work adopts AOMDV protocol as it assure for being loop-free and link-disjoint. Also, capability to notice disjoint paths without using source routing, low inter-nodal synchronization expenditure over AODV to obtain alternate paths are also included in this work.

3.3 Grey wolf optimization

In this research work, the social activity of grey wolves is described to form clustering mechanism. For performing clustering operation certain features are taken such as node’s mobility speed, direction, and location information. The mobile node is not allowed to be in more than one cluster. In every cluster there will be a mobile node named as cluster head (CH) which will manage the whole cluster and also the mobile nodes that belong to it. Four kinds of grey wolves such as alpha, beta, delta, and omega are engaged for simulating the leadership ladder. The alpha (α) wolves is considered as the leader of the pack because it take decisions about the actions and behavior of other wolfs in the group. The second rank in the hierarchy of grey wolves is beta (β) wolves. When the alpha wolves passes away or becomes very old beta wolf is considered as the best candidate. The beta follows the alpha's commands all over the pack and gives opinion to the alpha. Delta (δ) wolves or subordinate seen third in the hierarchy help to protect the complete pack. Senior delta wolf is promoted to beta wolf in case of death. The last rank in the hierarchy of grey wolves is Omega (ω) wolves. Death of delta wolf made the any one of the omega to delta. An omega (ω) wolf follows orders and instructions of a alpha, beta, delta wolves. Three main steps of hunting, are searching for prey, encircling prey, and attacking prey, are implemented to achieve optimization.

3.3.1 Social hierarchy

In order to accurately model the social hierarchy of wolves when manipulating GWO, we reflect on the fittest solution as the alpha (α). Accordingly, beta (β) wolf and delta (δ) wolf are the second and third best solutions respectively. The remaining of the candidate solutions are implicit to be omega (ω).The hunting optimization is guided by α, β, and δ. The ω wolves follow these three wolves.

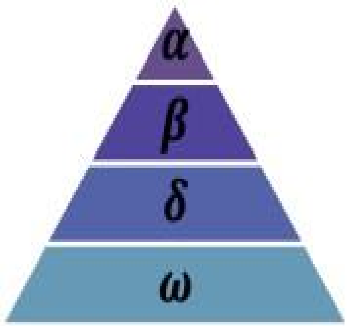

Fig.1. Social hierarchy

3.3.2 Encircling prey

During the course of hunting grey wolf encircle the prey as,

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

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

where t represents the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors , $\vec{X}_p$ is the position vector of the prey, $\vec{X}$ is the position vector of a grey wolf.

The vectors $\vec{A}$ and $\vec{C}$ are designed as follows:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \qquad (3)$$

$$\vec{C} = 2.\vec{r}_2 \qquad (4)$$

Where components of $\vec{a}\vec{a}$ are linearly decreased from 2 to 0 over the course of iterations and $\vec{r}_1$, $\vec{r}_2$ are random vectors in [0, 1].

By using the above equations, the grey wolf in the position of (X, Y) can update its position according to the position of the prey (X*,Y*). The positions are adjusted with the help of vectors $\vec{A}$ and $\vec{C}$.

3.3.3 Hunting the prey

Grey wolves have the ability to identify the position of prey and encircle them. The hunt is frequently guided by the alpha. The beta and delta may also contribute in hunting occasionally. For simulating the hunting behavior of grey wolves mathematically, the alpha, beta, and delta have better awareness about the probable location of prey. Hence, we keep the first three best solutions that obtained and force the other search agents to update their positions according to the position of the best search agent. The following formulas are projected in this regard.

$$\vec{D}_\alpha = |\vec{C}.\vec{X}_\alpha(t) - \vec{X}| \qquad (5)$$

$$\vec{D}_\beta = |\vec{C}.\vec{X}_\beta(t) - \vec{X}| \qquad (6)$$

$$\vec{D}_\delta = |\vec{C}.\vec{X}_\delta(t) - \vec{X}| \qquad (7)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.(\vec{D}_\alpha) \qquad (8)$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta) \qquad (9)$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3.(\vec{D}_\delta) \qquad (10)$$

$$\vec{X}_{(t+1)} = \frac{\vec{X}1 + \vec{X}2 + \vec{X}3}{3} \qquad (11)$$

Using the above equations, a search agent updates its position based on the alpha, beta, and delta in a n dimensional search space. The positions of alpha, beta, and delta in the search space are defined by the final position that would be in a random place within a circle. In other words alpha, beta, and delta estimate the location of the prey, and other wolves updates their positions accidentally around the prey.

3.1.4 Attacking prey (exploitation)

The grey wolves stop the hunt by attacking the prey when it stops moving. In order to mathematically model impending the prey we reduce the value of α. Note that the fluctuation range of A is also decreased by α. In other words A is a random value in the interval [-2a, 2a] where a is decreased from 2 to 0 over the course of iteration. When random values of A are in [-1, 1], the next position of the search agent can be in any position between its current position and the position of the prey.

3.3.5 Search for prey (exploration)

Grey wolves frequently investigate according to the position of the alpha, beta, and delta. They move away from each other to search for prey and come together to attack prey. In order to mathematically model deviation, we exploit A with random values larger than 1 or less than -1 to require the search agent to diverge from the prey. If the value of |A|>1, the grey wolves forces to diverge from the prey to hopefully find a fitter prey. If the value of |A|<1, the grey wolves forces to converge to the prey.

3.3.6 GWO Algorithm

- Define the grey wolf inhabitants Xi (i = 1, 2, ..., n)
- Initialize a, A, and C

- Determine the fitness of each search agent
- $X\alpha$ =the best search agent
- X_β =the second best search agent
- X_δ =the third best search agent
- while (t < Max number of iterations)
    - for each search agent
        - Update the location of the current search agent
    - end for
    - Update α, A, and C
    - Estimate the fitness of all search agents
    - Update $X\alpha$, X_β , and X_δ
    - t=t+1
    - end while
- return

3.3.7 GWO Flow Diagram

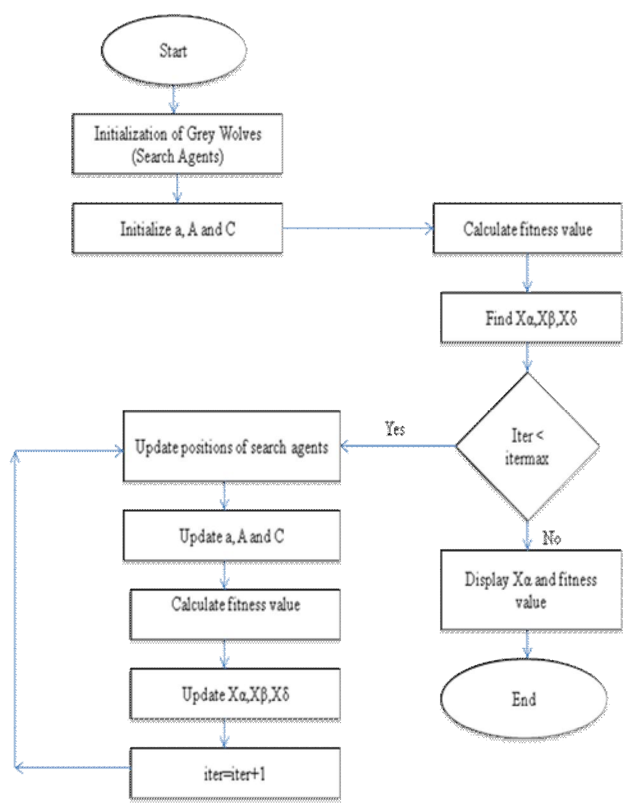

Fig.2. Flow Diagram of GWO

3.1.8 BLOCK DIAGRAM

Initially, 100 nodes are created and the random network was deployed. If a node wants to communicate with a node that is not openly within its communication range, it uses transitional nodes as routers. For cluster formation certain parameters such as node's speed, location information, position, and direction are noted. 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. Then initialize the GWO parameters of alpha (α), beta (β) and delta (δ) nodes. The fitness of grey wolf is calculated and create initial population of grey wolf as $X\alpha$, X_β , and X_δ . The first three best solutions are saved and rest is obliged to update their position according to the position of the best search agents. When the current iteration is less than the maximum iteration display the alpha ($X\alpha$) fittest value and selects the best path for routing.

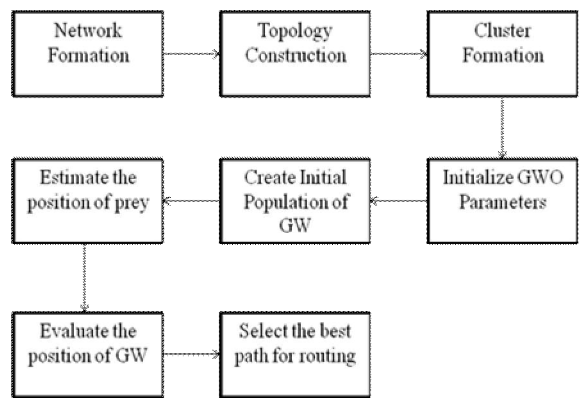

Fig.3. Block Diagram of GWO

IV. RESULTS AND DISCUSSION

4.1 Simulation Model and Parameters

In this simulation, the Constant Bit Rate (CBR) is utilized as a traffic source with 100 mobile nodes that are deployed over 1000X1000 meter terrain space. IEEE 802.11 MAC standard is employed with the bandwidth of 2 Mb/s and the packet size is fixed to 512 bytes that transmit in constant bit rate fashion. The transmission range of the nodes was set to 250m with the initial energy level of mobile nodes of 10 joules. The simulation settings are presented in Table-1.

Table-1 Simulation Settings

Parameter	Value
Standard	IEEE 802.11 standard
Area size	1000m X 1000m
Packet size	512 bytes
Traffic type	Constant Bit Rate
Transmission range	250m
Number of nodes	100
Simulation time	2ms
Speed	4ms
Initial Energy	10 joules
Bandwidth	2 Mb/s
Mobility type	Random waypoint model

4.2 Performance Analysis

The proposed work is implemented in Network Simulator Version 2. In this simulation, to define the network parameters and topology such as traffic source, number of nodes, queue size, node speed, routing protocols used and many other parameters an OTcl script has been written. Two files are produced when running the simulation, trace file for processing and a network animator (NAM) to visualize the simulation. NAM is a graphical simulation display tool.

4.2.1 Packet Delivery Ratio

Packet Delivery Ratio is the ratio of the data packets that were delivered to the objective node to the data packets that are generated by the source. It shows a routing protocol's feature in its delivery of data packets from source to destination. The higher the ratio, the performance of the routing protocol will enhance. PDR is calculated by

$$PDR = \frac{\text{No of packets received}}{\text{No of packets send}} * 100$$

4.2.2 Throughput

Throughput is known as the number of bits that the destination has effectively received. It is uttered in kilobits per second (Kbps). Throughput deals with a routing protocol's competence in receiving data packets by destination.

$$TP = \frac{(\text{No of bytes received} * 8)}{\text{simulation time}} * 1000\text{kbps}$$

4.2.3 Network Life Time

The network lifetime refers to the duration from the deployment to the moment when the network is considered as nonfunctional which is intended using the following formula:

Network lifetime $= \sum_{i=1}^{n}(\text{ene}(i) = 0)$

where, $\text{ene}(i) =$ Residual energy of a node

4.2.4 Routing Overhead

Routing overhead is the number of routing packets required for network communication. It is the ratio of the total number of packets rejected to the number of packets send. This study analyzed the average number of routing packets that is required to deliver a single data packet. This metric gave an idea about the more bandwidth that is devoted by the overhead in order to deliver data traffic. The routing overhead has an effect on the network's robustness in terms of the bandwidth exploitation and battery power consumption of the nodes.

$$\text{Routing Overhead} = \frac{\text{number of routing packets}}{\text{No of routing packets} + \text{No of packets sent}} * 100$$

4.2.5 End-to-end delay

End-to-End delay refers to the average time taken by data packets in successfully transmitting messages across the network from source to destination. This includes delays such as queuing at interface queue, promulgation and convey times, MAC retransmission delays, and buffering through the route discovery latency. The End to end delay can be calculated using the following formula:

End to end delay $= \sum_{i=1}^{n}(\text{Ri} - \text{Si})/n$

where,

$\text{Ri} =$ number of packets at destination

Si = number of packets send by source

n = total number of packets

4.2.6 Energy Consumption

Energy consumption refers to the quantity of energy that is used up by the network nodes within the simulation time. The consumption of mobile node energy is obtained by calculating each node's energy level at the end of the simulation. The following formula will construct the value for energy consumption:

$$\text{Energy consumption} = \sum_{i=1}^{n}(\text{ini}(i) - \text{ene}(i))$$

where ini(i) = Initial energy of a node
ene(i) = Residual energy of a node

4.3 Experimental Results

4.3.1 Packet Delivery Ratio

Fig.5 (a) shows the packet delivery ratio for AOMDVGWO and AOMDVPSO. The AOMDVGWO routing protocol selects the most stable route toward the destination. It has high packet delivery ratio than AOMDVPSO. The selected route has highest energy level and it consumes less energy than other routes. This reduces the possibilities of packet loss and link failure.

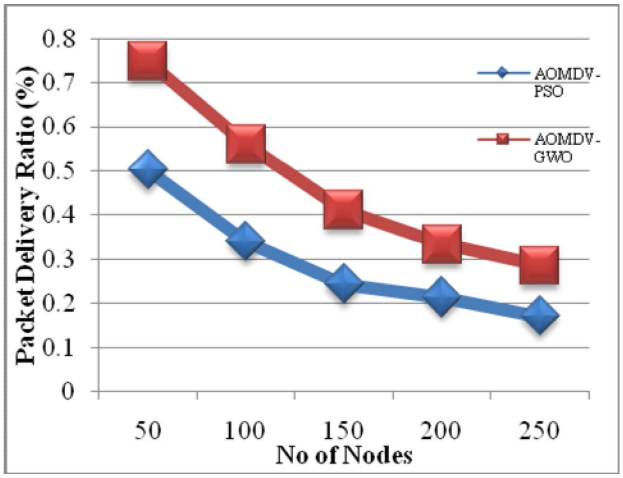

Fig.4 (a) Packet Delivery Ratio

4.3.2 Throughput

Fig.5 (b) shows the variation of throughput for AOMDVGWO and AOMDVPSO. These protocols have different throughput when increasing the node speed. The AOMDVGWO routing protocol performs better than AOMDVPSO in terms of throughput. As the route is strong, short and stable, the throughput will be at its maximum level.

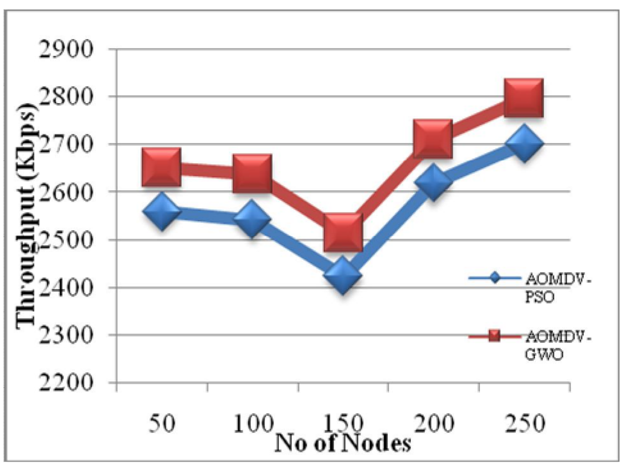

Fig.4 (b) Throughput

4.3.3 Network Life Time

Fig.5 (c) shows the variation of Network Life Time for AOMDVGWO and AOMDVPSO. The number of exhausted nodes increases when the node speed increases. The AOMDVGWO routing protocol performs better than AOMDVPSO in terms of Network Life Time. The AOMDV uses the nodes with high energy for data communication and it keeps the low energy nodes for later use.

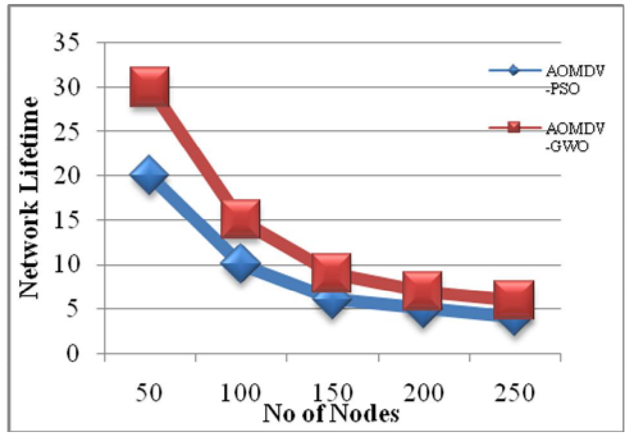

Fig.4 (c) Network Life Time

4.3.4 Routing Overhead Ratio

Fig.5 (d) shows the variation of Routing Overhead Ratio for AOMDVGWO and AOMDVPSO. When the node speed increases the Routing Overhead Ratio also increases. The AOMDVGWO protocol has low Overhead Ratio compared to the AOMDVPSO. Hence the possibility of route failure becomes almost minimal with less route discovery process.

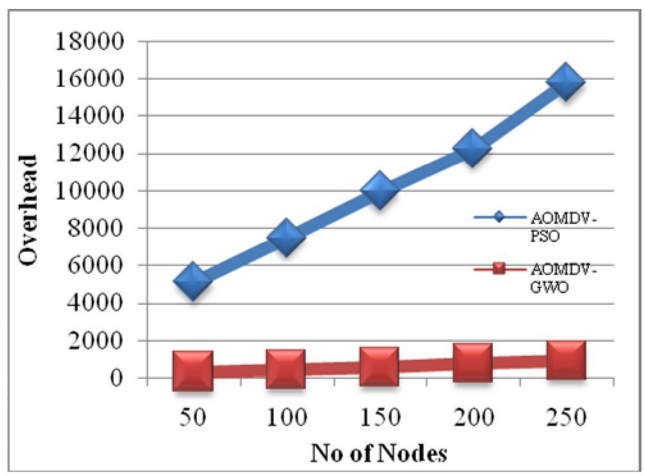

Fig.4 (d) Routing Overhead

4.3.5 End-to-end delay

Fig.5 (e) shows the variation of End-to-end delay for AOMDVGWO and AOMDVPSO. When the node speed increases the End-to-end delay also increases. The AOMDVGWO has less End-to-end delay compare to the AOMDVPSO.

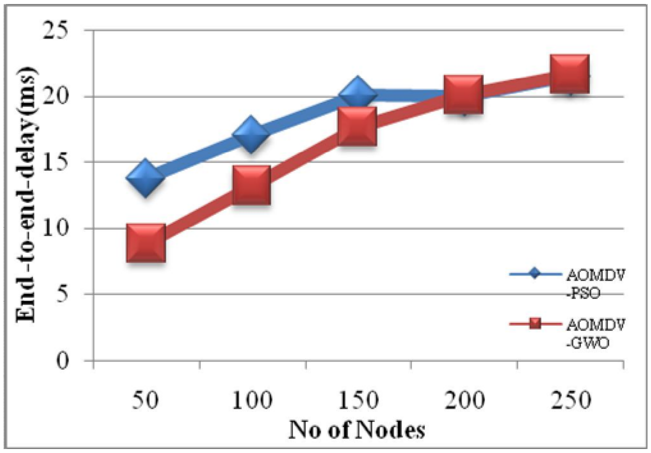

Fig.4 (e) End-to-end delay

4.3.6 Energy Consumption

Fig.5 (f) shows the variation of Energy Consumption for AOMDVGWO and AOMDVPSO. Energy Consumption of the mobile nodes increases when the node speed increases. While transmitting the data packets, the cluster head node send the packets through the high energy level nodes. This consumes less energy and enhance the node reliability.

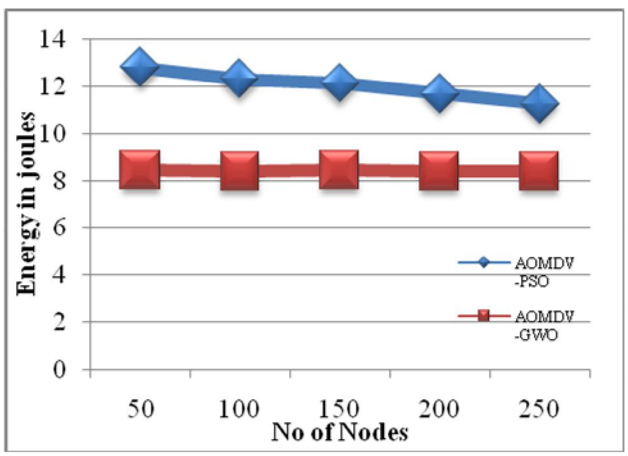

Fig.4 (f) Energy Consumption

V. CONCLUSION

In this paper, we have introduced a solution for the problem of routing in an ad hoc network. Mobile ad hoc networks are characterized by their dynamicity and lack of infrastructure. As the mobile nodes do not posses permanent power supply, energy consumption is considered as one of the major limitation. An energy efficient multipath routing scheme, called AOMDV-GWO using clustering mechanism is proposed to reveal the optimal route and ensure the reliability in MANET. 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. Simulation results show that the proposed AOMDV-GWO scheme performed much better than the existing scheme in terms of packet delivery ratio, throughput, End-to-End delay, routing overhead, energy consumption and network lifetime.

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