Wireless Personal Communications (2021) 120:1291–1312
https://doi.org/10.1007/s11277-021-08515-y

# An Optimized Communication Scheme for Energy Efficient and Secure Flying Ad-hoc Network (FANET)

**Mayank Namdev**[1] · **Sachin Goyal**[2] · **Ratish Agarwal**[2]

Accepted: 13 April 2021 / Published online: 24 April 2021


## Abstract
FANET (flying ad-hoc network) has provided broad area for research and deployment due to efficient use of the capabilities of drones and UAVs (unmanned ariel vehicles) in several military and rescue applications. Drones have high mobility in 3D (3 dimensional) environment and low battery power, which produce various problems such as small journey time and infertile routing. The optimal routing for communication will assist to resolve these problems and provide the energy efficient and secure data transmission over FANET. Hence, in this paper, we proposed a whale optimization algorithm based optimized link state routing (WOA-OLSR) over FANET to provide optimal routing for energy efficient and secure FANET. The efficiency of OLSR is enhanced by using WOA and evaluated performance shows the better efficiency of WOA-OLSR in terms of some parameters such as a packet delivery ratio, end to end delay, energy utilization, throughput, and time complexity against the previous approaches OLSR, MP-OLSR, P-OLSR, ML-OLSR-FIFO and ML-OLSR-PMS.

**Keywords** Drones · FANET · Whale Optimization · UAVs · OLSR · Throughput · Optimal Routing

## 1 Introduction

The multifarious and rising UAVs [1, 2] are utilized for the feasible and consistent communication over FANET. A multifarious system structure is used to provide a UAV abundant network communicating with various functional applications such as military, rescue, and disaster management on the basis of several topological investigations [3]. UAVs can be seen as a future of IoT (internet of things) communication in which 5G technology is used to enhance the performance of audio and video data transmission. The problems of UAVs like privacy and transmission volatility are diminished by using multiple UAVs depend on on-demand routing over FANET [4]. The transmission cost and capriciousness of the UAV is enhanced due to packet collision in 3D environment. The packet collisions are reduced

✉ Mayank Namdev
mayank.namdev@gmail.com

1 Department of CSE, University Institute of Technology, RGPV, Bhopal 462023, India

2 Department of IT, University Institute of Technology, RGPV, Bhopal 462023, India

by developing a decentralized 3D-SWAP approach in a simulator with unrestrained conditions such as strident positioning and breeze gusts [5]. UAV`s ecological information confirms the collection and communication of data packets for exploration and rescue processing in delay tolerant networks (DTN) concept [6]. Proactive coverage areas (PCAs) based DBS (drone base station) is developed to perform dynamic load processing on the basis of supply demand. The exposure region and elevation of DBS is obtained minimum energy utilization and momentous complexity diminution [7]. Drones are a unique kind of UAVs with higher velocity and dynamic environment utilizing for moving desired object detection in the minimum time interval [8]. The wireless sensor network (WSN) is integrated with the help of UAVs to enhance the area of network and overall performance. The clustering is processed with cluster heads and members selection for route distance and transmission time generation in WSN [9].

Efficient clustering also provides the hierarchical routing to diminish the overhead of mobile ad-hoc network (MANET) [10]. The offloading approach is used in drones to obtain privacy and minimum time utilization for data packet transmission over [11, 12] based clustering network (GWOCNET) based on grey wolf nature and node`s mobility in vehicular ad-hoc network (VANET). The outputs describe the better efficiency of GWOCNET against CLPSO (comprehensive learning particle swarm optimization) and MOPSO (Multi Objective PSO) [13]. K-Means is one of the popular clustering methods based on dynamic transmission ranges and applied on energy utilization of UAVs. The output shows the better performance of ECRNET (energy based clustering for network) based on number of clusters, cluster lifetime and creation time and power utilization versus CACONET (ant colony optimization based clustering for network) and GWOCNET approaches [14]. Numerous routing protocols [15, 16], which are responsible for information exchanging, path generation and secure communication, are developed for FANETs in the recent past years. The unpredictable and arbitrarily velocity of UAV are general challenges of FANET. These issues should be reduced by using proper routing between UAV through optimization approach [17].

The FANET [18] is a scalable and a feasible communication network among high velocity drones (UAVs) [8,19] in the 3 D structure. Routing is a most significant issue in FANET and most of the routing problems are resolved by using different topological architectures enhancing the throughput, and packet delivery ratio on OPNET (optimized network engineering tools) platform [20]. Routing is performed on the basis of AODV (ad-hoc on-demand distance vector) and OLSR (optimized link state routing) routing protocols for calculating the shortest paths from sources to destinations over FANET for higher packet delivery ratio (PDR) against number of UAVs, velocity and transmission ranges [21]. Another routing protocol ADRP (Adaptive density based routing protocol) is performed the qualitative [22] and effective data transmission over FANET. ADRP is implemented on a NS-2 simulator and the results are analyzed on the basis of the packet delivery ratio, and end to end delay against the AODV. Multi path OLSR (MP-OLSR) is also used for efficient routing among UAVs [23]. It is an enhanced version of OLSR which is capable of exchanging fire exposure data from GPS through a Fog or Edge environment for security and disaster management [24].

A stochastic model is combined with dynamic delay inhibited routing in which sender transmits the data packets utilizing local information only [25]. The routing of video and audio transmission has utilized large energy for path failures and network extrication. UAVs are used to charge the IoT things in less time slice maximum possible energy. Wireless technology is used to charge and recharge the IoT devices [26]. The ground and flying ad hoc network are combined to form an ambient network G-FANET which is used neural, genetic and fuzzy strategies to perform complex tasks. The feedback and learning rate of network is calculated for UAVs in terms of simulation time [27]. P-OLSR (predictive OLSR) is used to improve the quality of wireless link based on speed, direction and location of UAVs [28]. A fluid topology is implemented for selecting the neighbours of UAVs utilizing a metric SW-ETX (Speed Weighted Expected Transmission Count). Another improvement in OLSR, called ML-OLSR (mobility and load aware OLSR) [29], is introduced which selects the minimum mobility nodes and reduces the transmission loads and delay with enhancing the packet delivery. The performance of ML-OLSR is enhanced by using FIFO (first in first out) (ML-OLSR-FIFO) and PMS (prioritizing based message scheduling) (ML-OLSR-PMS) for providing reliable and flexible message transmission. The ML-OLSR-PMS approach combines the message priority assignment and scheduling modules in which message priority is decided, after that message is rescheduled in a desired output row [29].

In above survey, several approaches like OLSR, MP-OLSR, P-OLSR, ML-OLSR-FIFO, and ML-OLSR-PMS are introduced to perform optimal routing. The best drones are selected for routing on the basis of some parameters like energy utilization, mobility, and neighbourhood degree, but all the above proposed approaches is not utilized all the parameters together. The security is also not considered proper in proposed approaches. Hence, we proposed a whale optimization algorithm on optimized link state routing (WOA-OLSR) in which WOA is applied to multi objective function combining the several parameters such as neighbourhood benefaction, energy, stability time and key utilization of drones. The results are compared against previous approaches OLSR, MP-OLSR, P-OLSR, ML-OLSR-FIFO and ML-OLSR-PMS on the basis of packet delivery ratio, throughput, and end to end delay and energy utilization.

The remaining paper is as follows. The 2nd part illustrates the WOA approach mathematically with algorithm. The 3$^{rd}$ part describes the proposed WOA-OLSR in brief utilizing flowchart and algorithms. The 4th part illustrates the results obtained from the MATLAB simulation of WOA-OLSR. The 5th part explains conclusion of research paper.

## 2 Whale Optimization Algorithm (WOA)

The WOA is a freshly anticipated optimization technique imitating humpback whales the hunting procedure and behaviour. Whales are very intellectual emotive animal due to spindle cells and survive unaccompanied or in groups. The bigger humpback whale is as long as a school bus and prey the krill and tiny fish crowd. The hunting mechanism of humpback whales are also known as bubble net feeding, which is mathematically explained to perform optimization.

## 2.1 Encircling Prey

The preys positions can be discriminated by Humpback whales and enclose them. WOA supposes that the present best solution (search agent) represents as target prey and other search agents can be modified their locations to optimal solution. The activities are illustrated by the equations (Eqs. (1) and (2)).

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

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

where t = present iteration, $\vec{X}_p$ = prey position vector, $\vec{X}$ = Whale position vector, $\vec{D}$ = distance between prey and position of whale and $\vec{A}$,$\vec{C}$ are coefficient vector calculated by using Eq. (3) and (4).

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{3}$$

$$\vec{C} = 2.\vec{r}_2 \tag{4}$$

Here the coefficients of $\vec{a}$ are linearly reduced from 2 to 0 and $\vec{r}_1$, $\vec{r}_2$ indicates the random value vectors in [0, 1].

## 2.2 Bubble-Net Feeding Mechanism (Exploitation State)

It describes two approaches as follows:

I. Shrinking encircling method: This is done by reducing the value of $\vec{a}$. The variation assortment of $\vec{A}$ is also reduced by $\vec{a}$ to generate the value in interval [−a, a]. Assuming the values of $\vec{A}$ in [− 1, 1], the new location of whale (search agent) can be explained somewhere in between actual location of the agent and location of the present best agent.
II. Spiral modifying location: Initially it evaluates the location of prey ($\vec{X}^*$, $\vec{Y}^*$) and whale ($\vec{X}$, $\vec{Y}$). After that a spiral equation is generated between location of prey and whale to imitate the humpback whales helix wrought movement (Eq. (5)).

$$\vec{X}(t+1) = \vec{D'}.e^{bt}\cos(2\Pi t) + \vec{X}^*(t) \tag{5}$$

Here $\vec{D}' = \left|\vec{X}^*(t) - \vec{X}(t)\right|$ which denotes the distance between $i^{th}$ whale and current best prey, b = constant for explaining the logarithmic spiral shape and t = arbitrary number in interval [−1, 1].

The humpback whales spin in the region of prey inside a flinch circle and beside a spiral-shaped route concurrently. Therefore, we supposed that whales are modifying their locations during optimization with 50% probability of selection flinch circle or spiral model (Eq. 6).

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A}.\vec{D} & p < 0.5 \\ \vec{D}' e^{bt} \cos(2\Pi t) + \vec{X}^*(t) & p \geq 0.5 \end{cases} \tag{6}$$

Here p = arbitrary number in [0, 1].

The humpback whales are explored for prey arbitrarily as follows:

## 2.3 Prey Exploration

$\vec{A}$ is used to explore the prey and random exploration is utilized by whales for finding the locations of each other. Hence $\vec{A}$ is utilized (with arbitrary numbers $< -1$ & $> 1$) for exploration and $\left|\vec{A}\right| > 1$ is used for global search (Eqs. (7) and (8)).

$$\vec{D} = \left|\vec{C}.\vec{X}_{rand} - \vec{X}\right| \tag{7}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A}.\vec{D} \tag{8}$$

Here $\vec{X}_{rand}$ = arbitrary location vector (arbitrary whale).

The WOA initiates by utilizing a group of arbitrary solutions. In every repetition, whales (search agents) modify their locations according to arbitrary select whale or the best optimal whale. The value of parameter $\vec{a}$ is reduced from 2 to 0 instructing to obtain exploration and exploitation. If $\left|\vec{A}\right| > 1$, then arbitrary whale (search agent) is selected and the best solution is obtained for $\left|\vec{A}\right| < 1$ to modify the location of whales.

The WOA (algorithm 1) is described under the input parameters $N^i$ = number of iterations, $P^w$ = Whales population, $N^w$ = number of whales and output optimal whale (drone) ($X^*$).

| | **Algorithm 1. WOA Algorithm** | **Number of Operations** |
|---|---|---|
| 1. | **START** | |
| 2. | WHILE concluding condition is not satisfied | $(N^i + 1)$ |
| 3. | Given initial population values of whales (drones) $X_i (i = 1,2,3,.................., N_d)$ | |
| 4. | Given initial values of $a, A, l, c, p \,\&\, N^i$ | |
| 5. | Calculate the fitness of all whales | $N^i * P^w$ |
| 6. | $X^*$ = The best whale (search agent) | $N^i * N^w$ |
| 7. | WHILE (it < $N^i$) | $(N^i + 1)$ |
| 8. | FOR all whales (search agents) | $N^i * (N^w + 1)$ |
| 9. | If (p<0.5) | $N^i * N^w$ |
| 10. | If ($\lvert A \rvert < 1$) | $N^i * N^w$ |
| 11. | Modify the location of present whale (search agent) (eq. (1) (2) (3) & (4)) | $N^i * N^w$ |
| 12. | Else if ($\lvert A \rvert \geq 1$) | $N^i * N^w$ |
| 13. | Choose an arbitrary search agent ($\vec{X}_{rand}$) | $N^i * N^w$ |
| 14. | Modify the location of present whale (search agent) (eq. (7) & (8)) | $N^i * N^w$ |
| 15. | END IF | |
| 16. | Else if ($p \geq 0.5$) | $N^i * N^w$ |
| 17. | Modify the location of the present whale (search agent) (eq. (5)) | $N^i * N^w$ |
| 18. | END IF | |
| 19. | END FOR | |
| 20. | Calculate the fitness of all whales | $N^i * N^w$ |
| 21. | Modify $X^*$ if there exists a better location | $N^i * N^w$ |
| 22. | it = it+1 | $N^i$ |
| 23. | Modify $a, A, l, c \,\&\, p$ | $N^i$ |
| 24. | END WHILE | |
| 25. | END WHILE | |
| 26. | Return $X^*$ | $N^w$. |
| **27.** | **STOP** | |

## 3 Whale Optimization Algorithm on Optimized Link State Routing (WOA-OLSR)

The FANET is explained as a combination of drones, which are communicated with each other in a network area. Drones have a battery with fixed energy and moved into a 3D environment for data transmission. In our methodology, if a drone wants to send a packet to another neighbouring drone, then both of them have same key using for data packet encryption between them. It means a drone is used a single key for a single packet encryption and if drone want to send more than one packet, then it uses more than one key (one key for one packet). It enhances the security of data transmission through drones over FANET. The Whale Optimization Algorithm (WOA) is utilized to perform the optimal routing with optimized link state routing (OLSR) in FANET. WOA determines the optimal drones on OLSR routing with the help of the final significant weight of all drones on the basis of some parameters such as Drone`s Neighbourhood Benefaction, Drone`s Stability Time, Drone`s Energy and Drone`s Key Utilization. After that optimal drones have been utilized for maximum packet transmission to perform optimal routing over FANET.

### 3.1 System Model

The WOA-OLSR is performed in following steps:

#### 3.1.1 Drone`s Neighbourhood Benefaction

Neighbourhood benefaction of each drone is evaluated by obtaining the number of neighbour drones existing in every drone`s transmission range over FANET. If a drone has a large number of neighbour drones, then it is selected for maximum packet transmission with minimum energy consumption and negligible packet drop. Drone`s Neighbourhood Benefaction (DNB) is obtained by using Eqs. (9) and (10).

$$N\left(d_a\right) = \left\{d_b, \ni\, dis\tan ce\left(d_a, d_b\right) < TR_{d_a}\right\} \tag{9}$$

$$DNB(d_a) = \left|N(d_a)\right| \tag{10}$$

where $d_a$ and $d_b$ = $a^{th}$ and $b^{th}$ drone, $dis\tan ce(d_a, d_b)$ = distance between $d_a$ and $d_b$, $TR_{d_a}$ = transmission range of drone $d_a$, $\left|N(d_a)\right|$ = Number of neighbours of drone $d_a$, and $DNB(d_a)$ = DNB value of drone $d_a$.

#### 3.1.2 Drone`s Stability Time

Drone stability time (DST) is also related to the drone`s mobility. The drones are connected with other drones by several links and the estimated time of these links durations are used to obtain the stability time of each drone in an OLSR routing over FANET. It shows that larger the DST provides lesser the drone mobility with optimal routing. Firstly, the estimation time of link (ETL) is calculated by using Eq. (11), after that DST is evaluated by using Eq. (12).

$$ETL(d_a, d_b) = \frac{-(pq + rs) + \sqrt{(p^2 + r^2)(TR)^2 - (ps - qr)^2}}{p^2 + r^2} \tag{11}$$

where $ETL(d_a, d_b)$ = ETL between $a^{th}$ and $b^{th}$ drone, $p = S_{d_a} \cos\theta_{d_a} - S_{d_b} \cos\theta_{d_b}$ ,$q = d_{x_a} - d_{x_b}$,$r = S_{d_a} \sin\theta_{d_a} - S_{d_b} \sin\theta_{d_b}$, $s = d_{y_a} - d_{y_b}$ and TR = Transmission Range, $S_{d_a}$ & $S_{d_b}$ = Speed of $a^{th}$ and $b^{th}$ drone in the direction of $\theta_{d_a}$ and $\theta_{d_b}$, $d_{x_a}, d_{x_b}, d_{y_a}, d_{y_b}$ = $x^{th}$ and $y^{th}$ component of $a^{th}$ and $b^{th}$ drone.

$$DST(d_a) = \frac{\sum_{d_b=1}^{DNB(d_a)} ETL(d_a, d_b)}{DNB(d_a)} \tag{12}$$

where $DST(d_a)$ = DST of $a^{th}$ drone.

### 3.1.3 Drone`s Energy

A drone has optimally utilized for OLSR routing having maximum remaining energy over FANET. Drone`s Energy (DE) is calculated as a ratio of remaining energy to the DNB value of a drone at a particular time over FANET (Eq. (13)).

$$DE(d_a) = \frac{\mathrm{Re}maining\_Energy(d_a)}{DNB(d_a)} \tag{13}$$

where $\mathrm{Re}maining\_Energy(d_a)$ = remaining energy of $a^{th}$ drone and $DE(d_a)$ = DE of $a^{th}$ drone.

### 3.1.4 Drone`s Key Utilization

A drone has maximum number of keys utilizing for optimal OLSR routing. A single key is used to encrypt a single packet among drones over FANET. Different keys are used to encrypt the different packets between two drones. So Drone`s Key Utilization (DKU) is calculated by using Eqs. (14) and (15).

$$DKU(d_a) = \begin{cases} \sum_{k=1}^{K} DK_{d_a,k} & If\ \exists\, keys\ \in d_a \\ 0 & Otherwise \end{cases} \tag{14}$$

where

$$DK_{d_a,k} = \begin{cases} 1 & If\ K_k \in d_a \\ 0 & Otherwise \end{cases} \tag{15}$$

Here $DK_{d_a,k}$ = drone key relation which denotes the relation between $a^{th}$ drone and $k^{th}$ key, $K_k = k^{th}$ key from key group K, $DKU(d_a)$ = DKU value of $a^{th}$ drone.

### 3.1.5 Drone`s Final Significant Weight

Drone`s Final Significant Weight (DFSW) is obtained for each drone for OLSR routing over FANET by combining all the four parameters (DNB, DST, DE and DKU) to generate a multi objective function by Eq. (16).

$$Maximize\ DFSW = \left(\omega_1 * DNB\right) + \left(\omega_2 * DST\right) + \left(\omega_3 * DE\right) + (\omega_4 * DKU) \tag{16}$$

where $\omega_1$, $\omega_2$, $\omega_3$ and $\omega_4$ = weights of each parameter, so $\omega_1 + \omega_2 + \omega_3 + \omega_4 = 1$.

After obtaining multi objective function DFSW, WOA is applied on DFSW to determine optimal drones from the existing drones for optimal OLSR routing over FANET, which maximize the value of DFSW to obtain the best results. The drones are represented as whales in WOA. At last WOA is concluded by satisfying a concluding condition and optimal drones are found from giving drones over FANET.

### 3.2 Working and Operation

The flow chart of WOA-OLSR is shown in Fig. 1 and steps of WOA-OLSR working as follows:

*Step 1*: A Drone`s neighbourhood benefaction (DNB) is evaluated for a drone by using Eqs. (9) and (10).
*Step 2*: An estimation time of link (ETL) is generated for a drone by using Eq. (11), after that DST is calculated for a drone by using Eq. (12).
*Step 3*: A Drone energy (DE) is calculated for a drone using Eq. (13).
*Step 4*: A Drone`s key utilization (DKU) is calculated for a drone by using Eqs. (14) and (15).
*Step 5*: A Drone`s final significant weight (DFSW) is obtained for a drone by combining DNB, DST, DE and DKU generate a multi objective function by Eq. (16).
*Step 6*: Step 1 to step 5 is repeated for all drones over FANET and DFSW multi objective function for all drones is obtained.
*Step 7*: The WOA-OLSR is applied using a WOA algorithm (algorithm 1) to generate the optimal drones for optimal OLSR routing over FANET on the basis of multi objective DFSW function.

The Complete WOA-OLSR (algorithm 2) is illustrated with input parameters $N_d$ = Number of Drones as follows:

| **Algorithm 2.** The WOA-OLSR Routing Algorithm | **Number of Operations** |
|---|---|
| **START** | |
| FOR every drone | $(N_d + 1)$ |
| Calculate DNB value using eq. 9 & 10 | $N_d$ |
| Evaluate DST value using eq. 11 & 12 | $N_d$ |
| Evaluate DE value using eq. 13 | $N_d$ |
| Calculate DKU value (eq. 14 & 15) | $N_d$. |
| Obtain DFSW function by combining DNB, DST, DE and DKU value (eq. 16) | $N_d$ |
| END FOR | |
| FOR all drones | $(N_d + 1)$ |
| Apply WOA (algorithm 1) | |
| END FOR | |
| **STOP** | |

## 4 Result and Analysis

The proposed WOA-OLSR is developed through MATLAB 2018a environment to reasonably evaluate performance of OLSR routing over FANET. The WOA-OLSR performance is analyzed on the basis of several parameters listed in Table 1. The $N_d$ number of drones (30, 50, 80, 100, 150) is distributed over 1000 m * 1000 m and 2000 m * 2000 m area having 100–600 m transmission range and 0–60 m/s speed over FANET. The WOA-OLSR runs over 150 iterations with 150 population size of WOA.

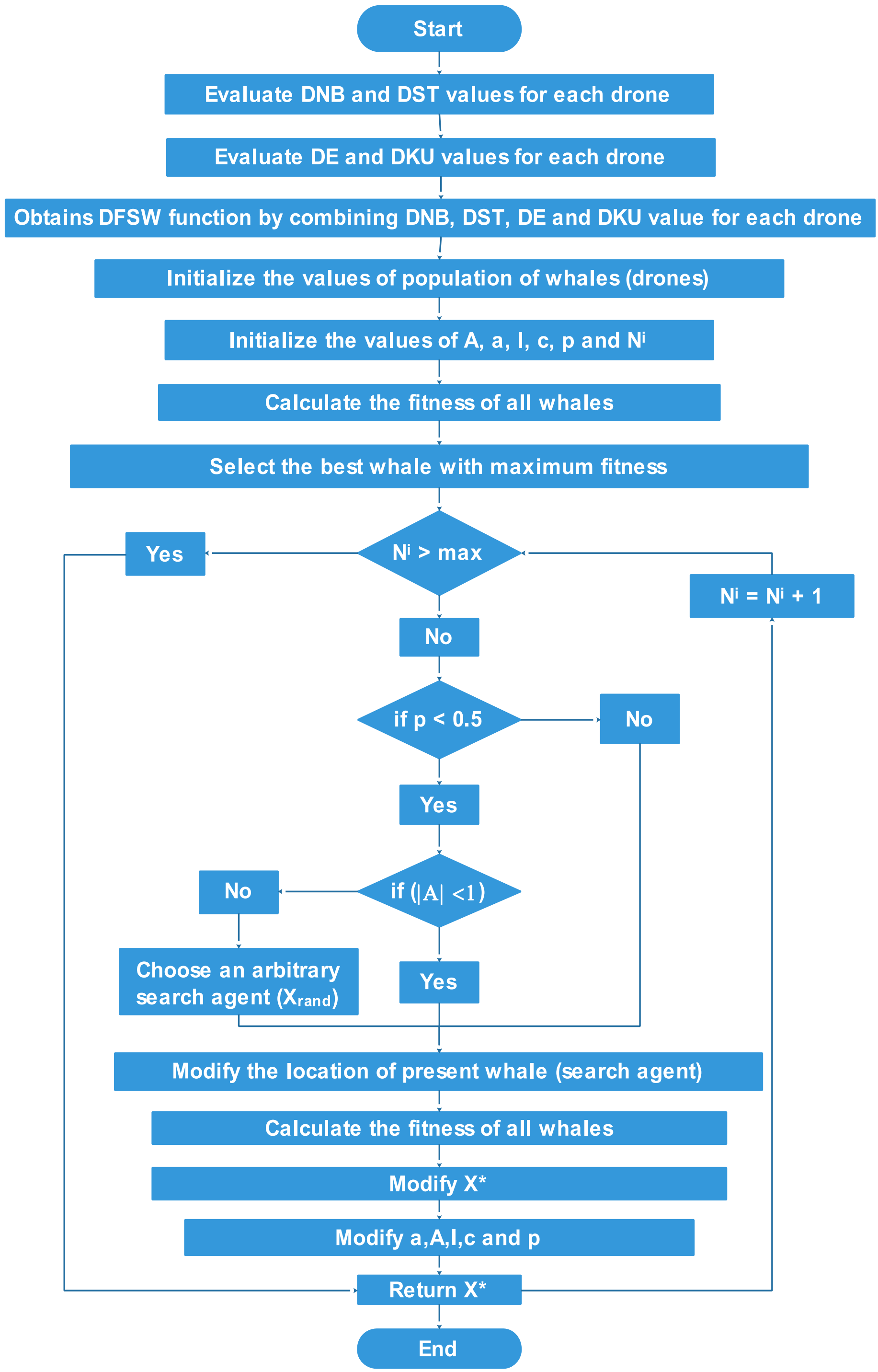


**Fig. 1** Flow chart of WOA-OLSR

**Table 1** Parameters of simulation

| Parameters of simulation | Values |
|---|---|
| Number of drones | 30, 50, 80, 100, 150 |
| Area of network | 1000 m * 1000 m and 2000 m * 2000 m |
| Drone`s speed | 0–60 m/s (randomly) |
| Transmission range | 100–600 m |
| Weights ($\omega_1$, $\omega_2$, $\omega_3$ and $\omega_4$) | 0.25, 0.25, 0.25, 0.25 |
| Size of WOA population | 150 |
| Number of iterations | 150 |

The WOA-OLSR is analyzed in terms of the packet delivery ratio, throughput, and end to end delay, energy utilization and time complexity against the results of other routing approaches OLSR, MP-OLSR, P-OLSR, ML-OLSR-FIFO, and ML-OLSR-PMS.

## 4.1 Packet Delivery Ratio (PDR)

PDR is defined as the fraction of sending data arrived at the base station in the data transmitted by all drones through optimal drones using OLSR in FANET. (Eq. 17)

$$PDR^t = \frac{Data^t_{BS}}{\sum_{i\in O_d}\sum_{j\in N_{d_i}} Data^t_j} \tag{17}$$

where $PDR^t$ = PDR (time t), $Data^t_{BS}$ = sending data arrived to base station (time t), $O_d$ = group of optimal drones, $N_{d_i}$ = group of all drones in $i^{th}$ optimal drone, & $Data^t_j$ = data transmitted by $j^{th}$ drone to base station (time t) using OLSR over FANET.

It shows that the WOA-OLSR generates the maximum PDR value of 93% for 1000 m ×ss 1000 m (Figs. 2, 3 and 4) and 91% for 2000 m × 2000 m (Figs. 5, 6 and 7) network area vs. the number of drones, transmission ranges and velocity ranges of drones as compare to several approaches OLSR (75% & 73%), MP-OLSR (81% & 79%), P-OLSR (83% & 81%), ML-OLSR-FIFO (85% & 83%), and MP-OLSR-PMS (87% and 85%).If the network area is increased, then value of PDR is reduced, because data a retransmitting more

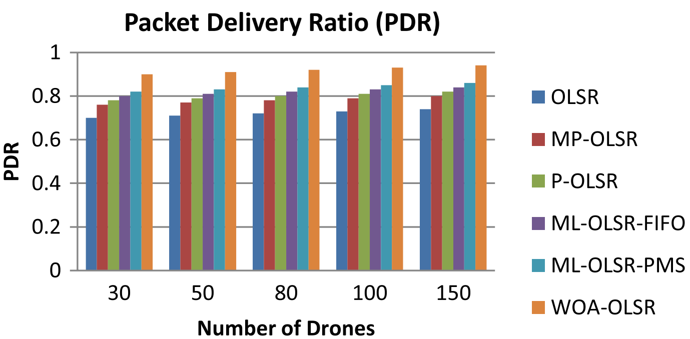


**Fig. 2** Packet delivery ratio vs. number of drones (1000 m × 1000 m network area)

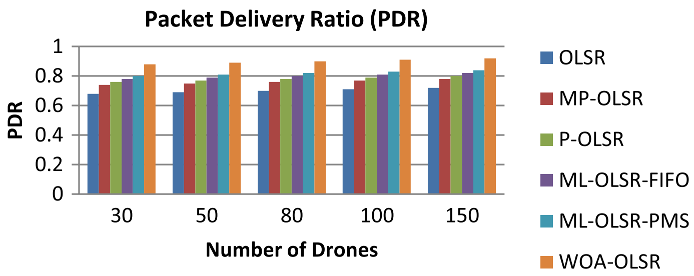


**Fig. 3** Packet delivery ratio vs. transmission ranges (1000 m × 1000 m network area)

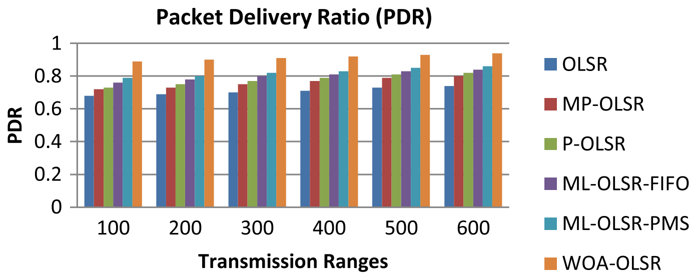


**Fig. 4** Packet delivery ratio vs. velocity ranges (1000 m × 1000 m network area)

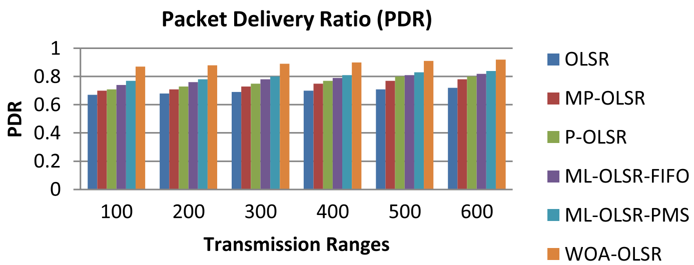


**Fig. 5** Packet delivery ratio vs. number of drones (2000 m × 2000 m network area)

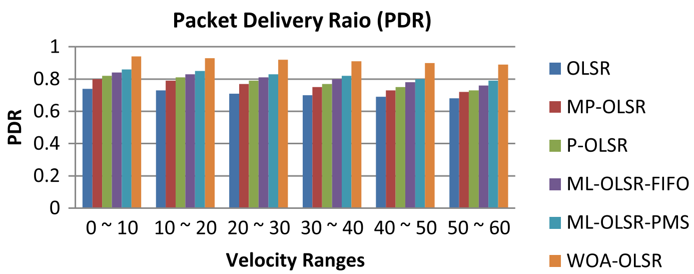


**Fig. 6** Packet delivery ratio vs. transmission ranges (2000 m × 2000 m network area)

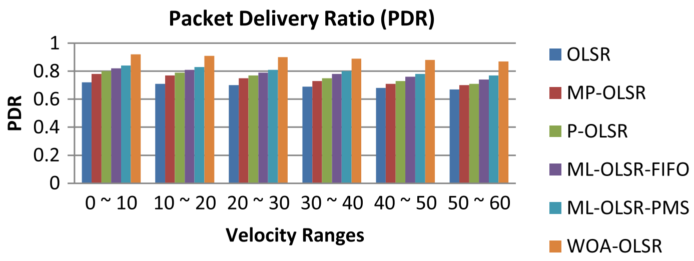


**Fig. 7** Packet delivery ratio vs. velocity ranges (2000 m × 2000 m network area)

distance decreasing the probability of delivery in larger network area. If the number of drones is enhanced, then value of PDR is enhanced, because having more drones to send the data. If the transmission ranges are increased, then value of PDR is enhanced, because having least numbers of drones to require for sending data increasing probability of packet delivery. If the velocity ranges are increased, then value of PDR is decreased, because having a maximum velocity of drones to require for sending data decreasing probability of packet delivery.

### 4.2 End to End Delay (EED)

EED is defined as a combination of path discovery and communication time through OLSR describing the association and ability of FANET. The minimum value of EED is selected for optimal OLSR routing.

It shows that the WOA-OLSR generates the minimum EED value (Seconds) of 0.2914 for 1000 m × 1000 m (Figs. 8, 9 and 10) and 0.3554 for 2000 m × 2000 m (Figs. 11, 12 and 13) network area vs. the number of drones, transmission ranges and velocity ranges of drones as compare to several approaches OLSR (0.4412 & 0.4689), MP-OLSR (0.4234 & 4521), P-OLSR (0.4004 & 0.4321), ML-OLSR-FIFO (0.3895 & 0.4195), and MP-OLSR-PMS (0.3843 and 0.4134). If the network area is increased, then value of EED is enhanced, because data are transmitting more distance in larger network area. If the number of drones is enhanced, then value of EED is enhanced, because having more drones to send the data. If the transmission ranges are enhanced, then value of EED is decreased, because having least numbers of drones to require for sending data. If the velocity ranges are increased,

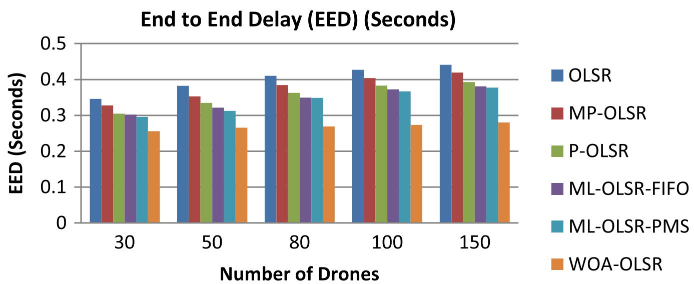


**Fig. 8** End to end delay vs. number of drones (1000 m × 1000 m network area)

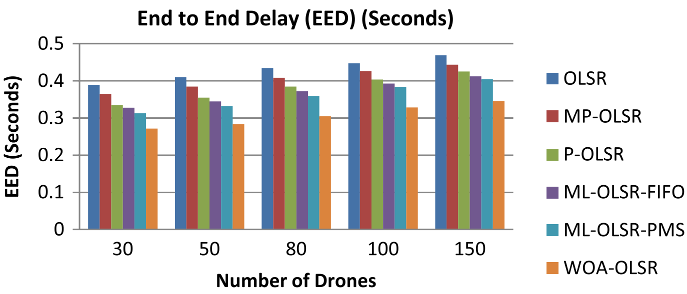


**Fig. 9** End to end delay vs. transmission ranges (1000 m × 1000 m network area)

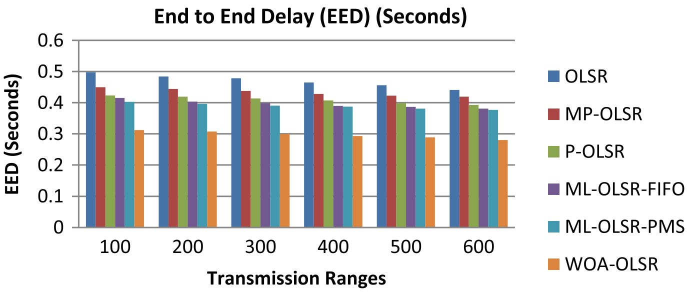


**Fig. 10** End to end delay vs. velocity ranges (1000 m × 1000 m network area)

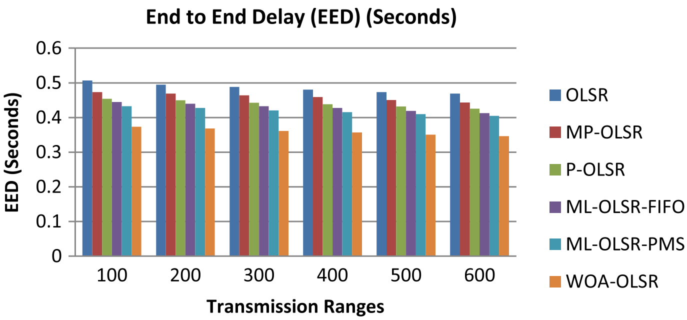


**Fig. 11** End to end delay vs. number of drones (2000 m × 2000 m network area)

then value of EED is increased, because having a maximum velocity of drones to require for sending data.

### 4.3 Energy Utilization

It is the energy utilized by drones for transmitting the data packets at a time through OLSR routing over FANET. The life and stability of optimal drones are increased by decreasing the energy utilization.

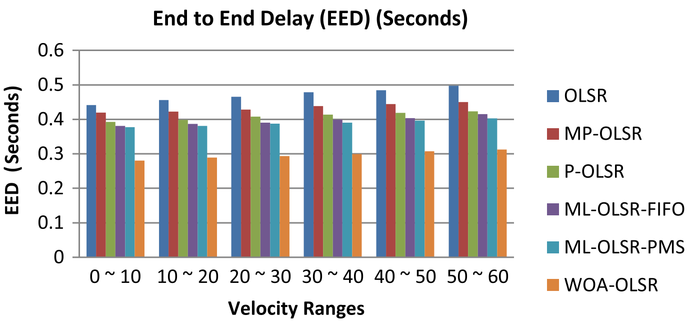


**Fig. 12** End to end delay vs. transmission ranges (2000 m × 2000 m network area)

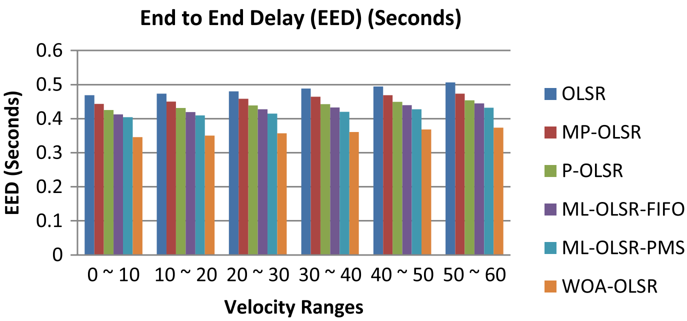


**Fig. 13** End to end delay vs. velocity ranges (2000 m × 2000 m network area)

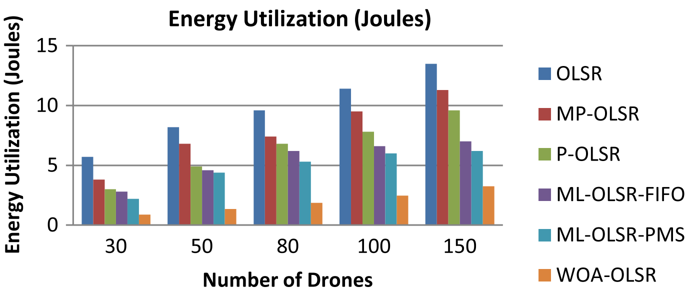


**Fig. 14** Energy utilization vs. number of drones (1000 m × 1000 m network area)

It shows that the WOA-OLSR generates the minimum Energy Utilization value (Joules) of 3.385 for 1000 m × 1000 m (Figs. 14, 15 and 16) and 3.684 for 2000 m × 2000 m (Figs. 17, 18 and 19) network area vs. the number of drones, transmission ranges and velocity ranges of drones as compared to several approaches OLSR (13.5 & 13.8), MP-OLSR (11.2&11.6), P-OLSR (9.8&9.3), ML-OLSR-FIFO (7.4 & 8.1), and MP-OLSR-PMS (6.4 and 7.4). If the network area is increased, then value of energy utilization is enhanced, because data are transmitting more distance in larger network area. If the number of drones

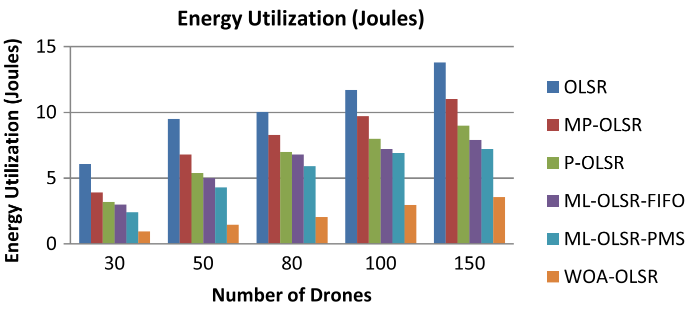


**Fig. 15** Energy utilization vs. transmission ranges (1000 m × 1000 m network area)

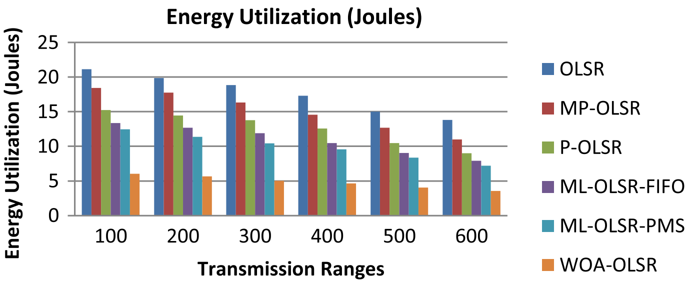


**Fig. 16** Energy utilization vs. velocity ranges (1000 m × 1000 m network area)

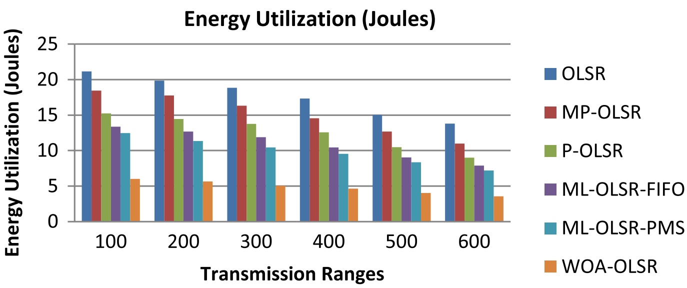


**Fig. 17** Energy utilization vs. number of drones (2000 m × 2000 m network area)

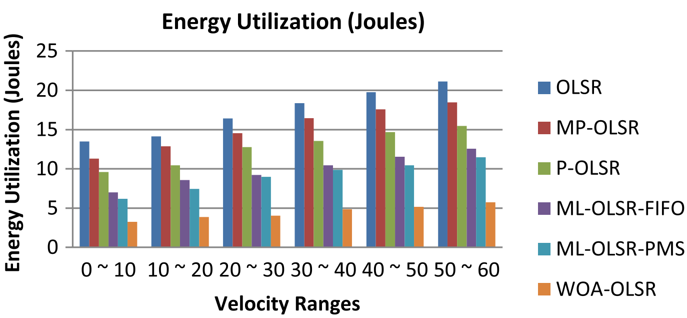


**Fig. 18** Energy utilization vs. transmission rsanges (2000 m × 2000 m network area)

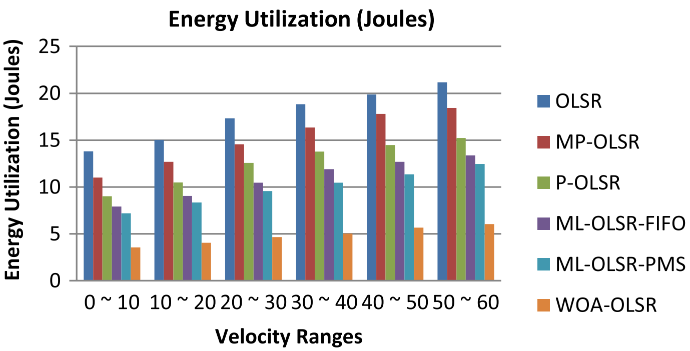


**Fig. 19** Energy utilization vs. velocity ranges (2000 m × 2000 m network area)

is enhanced, then value of energy utilization is enhanced, because having more drones consume the more energy. If the transmission ranges are enhanced, then value of energy utilization is decreased, because having more drones as neighbours. If the velocity ranges are increased, then value of energy utilization is increased, because having maximum velocity of drones to consume the more energy over FANET.

## 4.4 Throughput

It is the transferred data arrived to the base station per unit time slice and data is transferred by all drones through optimal drones using OLSR over FANET.

It shows that the WOA-OLSR generates the maximum throughput (bits per seconds) value of 11,657 for 1000 m × 1000 m (Figs. 20, 21 and 22) and 10,853 for 2000 m × 2000 m (Figs. 23, 24 and 25) network area vs. the number of drones, transmission ranges and velocity ranges of drones as compare to several approaches OLSR (6675 & 6435), MP-OLSR (7466 & 7234), P-OLSR (7857 & 7657), ML-OLSR-FIFO (8046 & 7845), and MP-OLSR-PMS (8435 and 8046). If the network area is increased, then value of throughput is decreased, because data are transmitting more distance decreasing the probability of delivery in larger network area. If the number of drones is enhanced, then value of throughput is increased, because having more drones to send the data. If the transmission ranges are increased, then value of throughput is increased, because having least numbers of drones to require for sending data increasing probability of packet delivery. If the velocity ranges

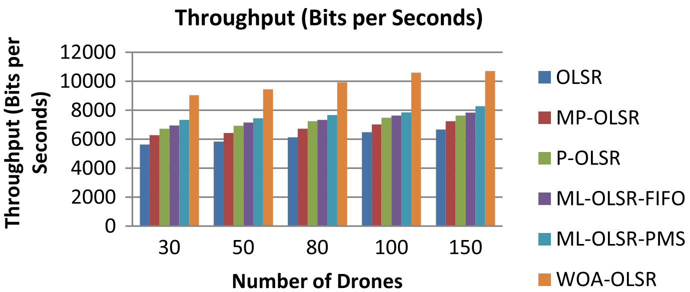


**Fig. 20** Throughput vs. number of drones (1000 m × 1000 m network area)

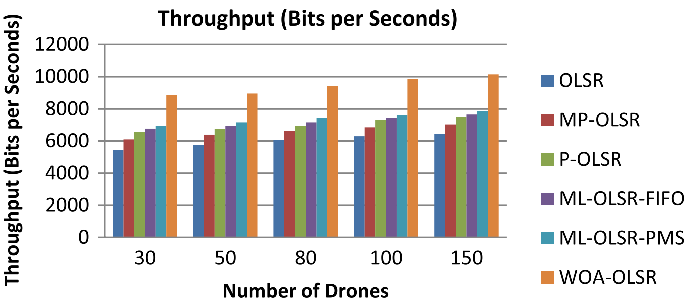


**Fig. 21** Throughput vs. transmission ranges (1000 m × 1000 m network area)

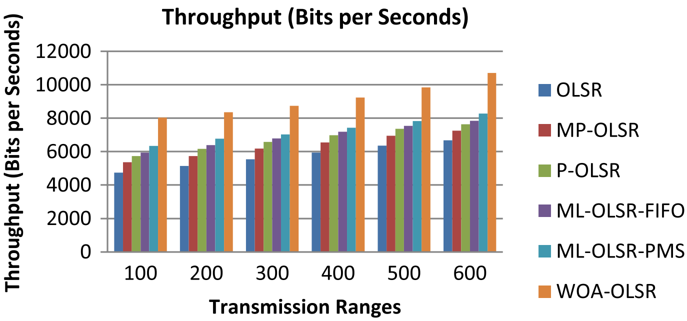


**Fig. 22** Throughput vs. velocity ranges (1000 m × 1000 m network area)

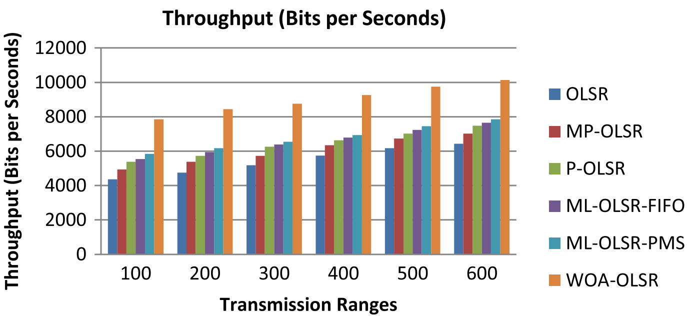


**Fig. 23** Throughput vs. number of drones (2000 m × 2000 m network area)

are increased, then value of throughput decreased, because having a maximum velocity of drones to require for sending data decreasing probability of packet delivery.

## 4.5 WOA-OLSR Time Complexity

The input values based running time of WOA-OLSR is evaluated as follows: $N^i$ = number of iterations, $P^w$ = Whales population, $N^w$ = number of whales, $N_d$ = number of

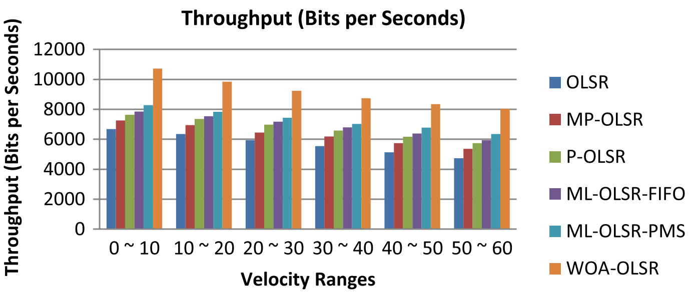


**Fig. 24** Throughput vs. transmission ranges (2000 m × 2000 m network area

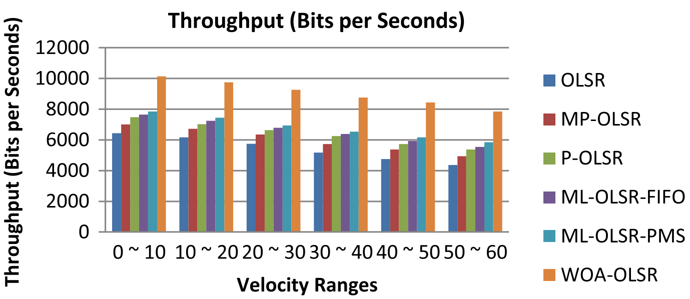


**Fig. 25** Throughput vs. velocity ranges (2000 m 2000 m network area)

drones,$D^e$ = elements of drone and step cost = 1 unit. Hence the total operation of WOA-OLSR is generated from algorithm 1 (Sect. 2.3 ) and algorithm 2 (Sect. 3.2).

$$\begin{aligned} Total - Operation = & N_d + 1 + N_d + N_d + N_d + N_d + N_d + N^i \\ & + 1 + N^i * P^w + N^i * N^w + N^i + 1 + N^i * (N^w + 1) \\ & + N^i * N^w + N^i * N^w + N^i * N^w + N^i * N^w + N^i * N^w \\ & + N^i * N^w + N^i * N^w + N^i * N^w + N^i * N^w \\ & + N^i * N^w + N^i + N^i + N^w \end{aligned}$$

$$Total - Operation = N^i * P^w + 12N^i * N^w + 6N_d + 5N^i + N^w + 3 \tag{18}$$

There is further $N_d * D^e$ operations are utilized to employ $N_d$ number of drones and $D^e$ elements of drones. Hence, Eq. 18 is converted to Eq. 19.

$$Total - Operation = N^i * P^w * N_d * D^e + 12N^i * N^w + 6N_d + 5N^i + N^w + 3 \tag{19}$$

The time complexity in the worst case is calculated by assuming the entire input values same in Eq. 19, so Eq. 20 is obtained.

$$Total - Operation = n^4 + 12n^2 + 3 \tag{20}$$

The time complexity of approaches is OLSR (O($n^2$)), MP-OLSR (O($n^2$)), P-OLSR (O($n^2$)), ML-OLSR-FIFO (O($n^3$)), and MP-OLSR-PMS (O($n^3$)) and WOA-OLSR (O($n^4$)). Hence, the solution of all approaches like OLSR, MP-OLSR, P-OLSR, ML-OLSR-FIFO, and MP-OLSR-PMS and WOA-OLSR are evaluated in polynomial time.

## 5 Conclusion

The capabilities of drones and UAVs are efficiently utilized for various military and rescue applications to enhance the research and development of FANET. The small journey time and infertile routing are basic problems of drones due to high mobility in a 3D environment and low battery power. The secure and energy efficient data transmission will be provided through optimal routing by resolving the problems of drones over FANET. Therefore, a whale optimization algorithm based optimized link state routing (WOA-OLSR) is proposed to obtain energy efficient and secure optimal routing in FANET. The calculated performance illustrates the better efficiency of WOA-OLSR based on some parameters such as a packet delivery ratio, end to end delay, energy utilization, throughput, and time complexity as compared to the previous approaches OLSR, MP-OLSR, P-OLSR, ML-OLSR-FIFO and ML-OLSR-PMS. In the future, developers can advance more than one objective as per their needs for energetic drones with maximum mobility. The routing mechanism in FANET is also improved by utilizing other bio inspired approaches like Fruit Fly Optimization, Moth-Flame Optimizer, Dragonfly Optimization, and Grey Wolf Optimization for future methodical studies.

**Funding** Not Applicable.

**Code Availability** Custom Code.

**Declarations**

**Conflict of Interest** The authors declare that they have no conflict of interest.

## References

1. Sharma, V., Sabatini, R., & Ramasamy, S. (2016). UAVs assisted delay optimization in heterogeneous wireless networks. *IEEE Communication Letters, 20*, 2526–2529
2. Khan, N. A., Jhanjhi, N. Z., Brohi, S. N., & Nayyar, A. (2020). Emerging use of UAV's: Secure communication protocol issues and challenges. In *Drones in Smart-Cities* (pp. 37-55). Elsevier.
3. Ahn, T., Seok, J., Lee, I., & Han, J. (2018). Reliable flying iot networks for UAV disaster rescue operations. *Mobile Information Systems*. https://doi.org/10.1155/2018/2572460
4. Erdelj, M., Uk, B., Konam, D., & Natalizio, E. (2018). From the eye of the storm: An IoT ecosystem made of sensors, smartphones and UAVs. *Sensors, 18*, 1–20. https://doi.org/10.3390/s18113814
5. Ferrera, E., Alcántara, A., Capitán, J., Castaño, A. R., Marrón, P. J., & Ollero, A. (2018). Decentralized 3D collision avoidance for multiple UAVs in outdoor environments. *Sensors, 18*, 1–20. https://doi.org/10.3390/s18124101
6. Bujari, A., Calafate, C. T., Cano, J. C., Manzoni, P., Palazzi, C. E., & Ronzani, D. (2018). A location-aware waypoint-based routing protocol for airborne DTNS in search and rescue scenarios. *Sensors, 18*, 1–14. https://doi.org/10.3390/s18113758
7. Hu, B., Wang, C., Chen, S., Wang, L., & Yang, H. (2018). Proactive coverage area decisions based on data field for drone base station deployment. *Sensors, 18*, 1–14. https://doi.org/10.3390/s18113917

8. Kim, B., Min, H., Heo, J., & Jung, J. (2018). Dynamic computation offloading scheme for drone-based surveillance systems. *Sensors, 18*, 1–10. https://doi.org/10.3390/s18092982
9. Popescu, D., Dragana, C., Stoican, F., Ichim, L., & Stamatescu, G. (2018). A collaborative UAV-WSN network for monitoring large areas. *Sensors, 18*, 1–25. https://doi.org/10.3390/s18124202
10. Huang, J., Fan, X., Xiang, X., Wan, M., Zhuo, Z., & Yang, Y. (2016). A clustering routing protocol for mobile ad hoc networks. *Mathematical Problems in Engineering*. https://doi.org/10.1155/2016/5395894
11. Ganesan, R., Raajini, X. M., Nayyar, A., Sanjeevikumar, P., Hossain, E., & Ertas, A. H. (2020). BOLD: Bio-inspired optimized leader election for multiple drones. *Sensors, 20*, 1–20
12. Valentino, R., Jung, W. S., & Ko, Y. B. (2018). A design and simulation of the opportunistic computation offloading with learning-based prediction for unmanned aerial vehicle (UAV) clustering networks. *Sensors, 18*, 1–14. https://doi.org/10.3390/s18113751
13. Fahad, M., Aadil, F., Khan, S., Shah, P. A., Muhammad, K., Lloret, J., Wang, H., Lee, J. W., & Mehmood, I. (2018). Grey wolf optimization based clustering algorithm for vehicular ad-hoc networks. *Computers and Electrical Engineering, 70*, 853–870
14. Aadil, F., Raza, A., Khan, M. F., Maqsood, M., Mehmood, I., & Rho, S. (2018). Energy aware cluster-based routing in flying ad-hoc networks. *Sensors, 18*, 1–16. https://doi.org/10.3390/s18051413
15. Albu-Salih, A. T., Seno, S. A. H., & Mohammed, S. J. (2018). Dynamic routing method over hybrid SDN for flying ad hoc networks. *Baghdad Science Journal, 15*(3), 361–368
16. Hong, J., Zhang, D., & Niu, X. (2017). Impact analysis of node motion on the performance of FANET Routing protocols. In: *14th International Conference on wireless Communications, Networking and Mobile Computing (WiCOM),* pp. 147–162.
17. Zheng, X., & Qi, Q., Wang, Q., Li, Y. (2017). An adaptive density based routing protocol for flying Ad Hoc networks. In: *2nd International Conference on Materials Science, Resource and Environment Engineering (MSREE) AIP Conf. Proc.*, pp. 1–8. http://doi.org/https://doi.org/10.1063/1.5005315
18. Perez, A. G., & Cano, M. D. (2018). Flying ad hoc networks: A new domain for network communications. *Sensors, 18*, 1–23. https://doi.org/10.3390/s18103571
19. Sharma, V., Kumar, R., & Rathore, N. (2018). Topological broadcasting using parameter sensitivity-based logical proximity graphs in coordinated ground-flying ad hoc networks. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 6*(3), 54–72
20. Khan, M. A., Khan, I. U., Safi, A., & Quershi, I. M. (2018). Dynamic routing in flying ad-hoc networks using topology-based routing protocols. *Drones, 2*, 1–15. https://doi.org/10.3390/drones2030027
21. Leonov, A. V., & Litvinov, G. A. (2018). Simulation-based packet delivery performance evaluation with different parameters in flying ad-hoc network (FANET) using AODV and OLSR. In: *International Conference Information Technologies in Business and Industry, IOP Conf. Series, Journal of Physics*, (pp. 1-16). Doi:https://doi.org/10.1088/1742-6596/1015/3/032178
22. Khan, M. A., Qureshi, I. M., & Khanzada, F. (2019). A hybrid communication scheme for efficient and low-cost deployment of future flying ad-hoc network (FANET). *Drones, 3*(16), 1–20. https://doi.org/10.3390/drones3010016
23. Yi, J., Adnane, H. A., David, S. & Parrein, B. (2018). Multipath optimized link state routing for mobile ad hoc network. *HAL,* 1–17.
24. Radu, D., Cretu, A., Parrein, B., Yi, J., Avram, C., & Astilean, A. (2018). Flying ad hoc network for emergency applications connected to a fog system. *HAL*, 1–13. (https://hal.archives-ouvertes.fr/hal-01763827)
25. Wen, S., & Huang, C. (2018). Delay-constrained routing based on stochastic model for flying ad hoc networks. *Mobile Information Systems*. https://doi.org/10.1155/2018/6056419
26. Arabi, S., Sabir, E., Elbiaze, H., & Sadik, M. (2018). Data gathering and energy transfer dilemma in UAV-assisted flying access network for IoT. *Sensors, 18*, 1–25. https://doi.org/10.3390/s18051519
27. Sharma, V., & Kumar, R. (2017). G-FANET: An ambient network formation between ground and flying ad hoc networks. *Telecommunication Systems, 65*(1), 31–54
28. Wei, Z., Liu, X., Han, C., & Feng, Z. (2018). Neighbor discovery for unmanned aerial vehicle networks. *IEEE Access, 6*, 68288–68301. https://doi.org/10.1109/ACCESS.2018.2871132
29. Li, J., Chen, M., Dai, F., & Wang, H. (2018). Prioritizing-based message scheduling for reliable unmanned aerial vehicles ad hoc network. *International Journal Perform ability Engineering, 14*(9), 2021–2029. https://doi.org/10.23940/ijpe.18.09.p10.20212029

**Mayank Namdev** was born in India in 1985. He has done his BE in Information Technology from BIST, RGPV Bhopal, M.Tech in Computer Science and Engineering from RKDFIST RGPV Bhopal and currently Ph.D. research scholar at the department of Computer Science Engineering in UIT RGPV Bhopal (MP), India. His research interest includes Ad Hoc Network, Data Base Security, Network Management and algorithm analysis.

**Sachin Goyal** was born in India in March 1979. He has done his BE in Computer Science & Engg From ITM, RGPV, Bhopal, M.Tech in Artificial Intelligence from SATI, RGPV, Bhopal and have done phD in IT from RGPV, Bhopal. His area of Interest includes Digital watermarking, Theoretical Computer science and computer network. He published More than 30 papers in Journals and Conferences (Including SCIE and SCOPUS Journals). He is presently working as a Associate professor in Department of Information Technology, UIT, Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal.


**Ratish Agarwal** was born in India in May 1979. He has done his BE in Electronics and Communication with honours from Rajiv Gandhi Technological University, Bhopal [M.P.], Qualified GATE in 2001 with 94%, MTech. [Digital Communication] First division with honours (80%) from MANIT, Bhopal [M.P.] and have done PhD from RGPV, Bhopal. His area of Interest includes Mobile Ad Hoc Network, Mobile Computing, Computer Architecture. He published More than 50 papers in Journals and Conferences (Including SCI and SCOPUS Journals). He is presently working as a Associate professor in Department of Information Technology, UIT, Rajiv Gandhi Proudyogiki Vishwavidyalaya, Bhopal.