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Highly Optimized Energy Saving Protocol for Flying ad-hoc Network

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***Abstract:** FANET has opened up a wide arena for the study and implementation of drone and UAV (unmanned aerial vehicle) efficiency in a variety of military and rescue applications. In this paper, we propose a hybrid energy-aware routing protocol. The approaches are based on two swarm intelligence methods: ant colony optimization (ACO) and particle swarm optimization (PSO). The performances of these approaches are compared with other bio-inspired feature selection methods based on ant colony optimization, particle swarm optimization, and grey wolf optimization. we propose a hybrid energy-aware clustering technique using a genetic algorithm for cluster formation and management. The proposed scheme shows better results as compared to other bioinspired clustering algorithms on the basis of evaluation benchmarks such as end-to-end latency, packet delivery ratio, energy consumption, time complexity, and throughput, and as a result, hybrid ACOPSO is used to enhance ACOPSO efficiency. The results indicate that the proposed scheme has improved throughput by 60% and 38% with respect to ant colony optimization and, grey wolf optimization, respectively. In terms of average cluster building time while average energy consumption has improved by 23% and 33% when compared to the ant colony optimization and grey wolf optimization, respectively. From the comparison graph, it is concluded that our proposed method has achievable throughput which is significantly increasing compared to other methods.*

***Keywords:** FANET, Whale optimization, UAVs, Routing protocol analysis, Genetic Algorithm.*

I. INTRODUCTION

FANETs are enhanced mobile ad hoc networks that utilize the airplane as a node for broadcasting, receiving, and forwarding wireless communication over the air. Data routing between UAVs is a substantial difficulty in a FANET, which is not the case in MANETs with low portable mobility circumstances. Routing tables must be dynamically updated in response to topology changes. Route reliability is also a major issue because of the increased mobility in FANET. Reliable routing protocol, but such routing approaches must be suitable for FANET [1]. To this end, developing a flexible and responsive ad hoc model necessitates new lines of study to compute routing metrics and create effective routing algorithms and network models. In such instances, each UAV must modify its flight route, and new ones must be computed incrementally [2]. As a result, new methods/algorithms for arranging FANET nodes for structuring UAV clusters are necessary. FANET with UAV clustering network as shown below in Fig.1[3][4].

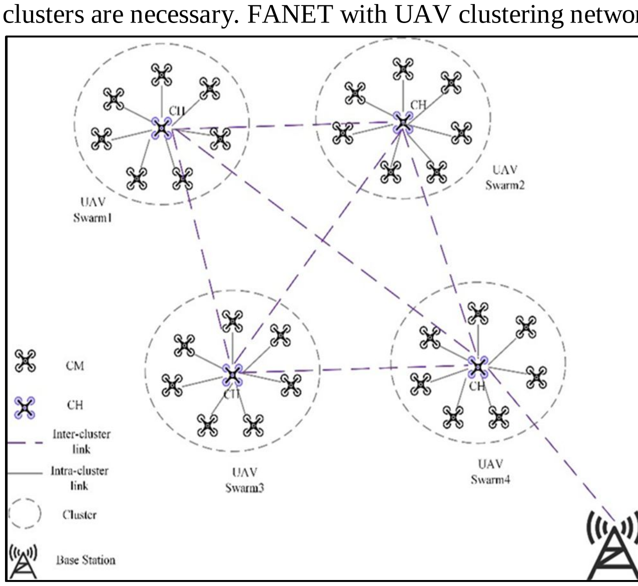

Figure1. FANET Clustering Architecture

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The rest of the paper is organized as follows: Section 2 presents the existing work on the clustering algorithms in UAV communication. Section 3 describes the proposed hybrid clustering algorithm in detail, including the calculation of the optimal number of paths, and Energy efficient cluster management mechanism. Simulation results and performance analysis are given in Section 4. Section 5 provides the conclusion and the outlook for future work.

II. LITREATURE SURVEY

A. *Optimization Techniques*

Numerous optimization approaches are utilized to discover optimal solutions. The following is optimization strategy that falls under the category of these algorithms.

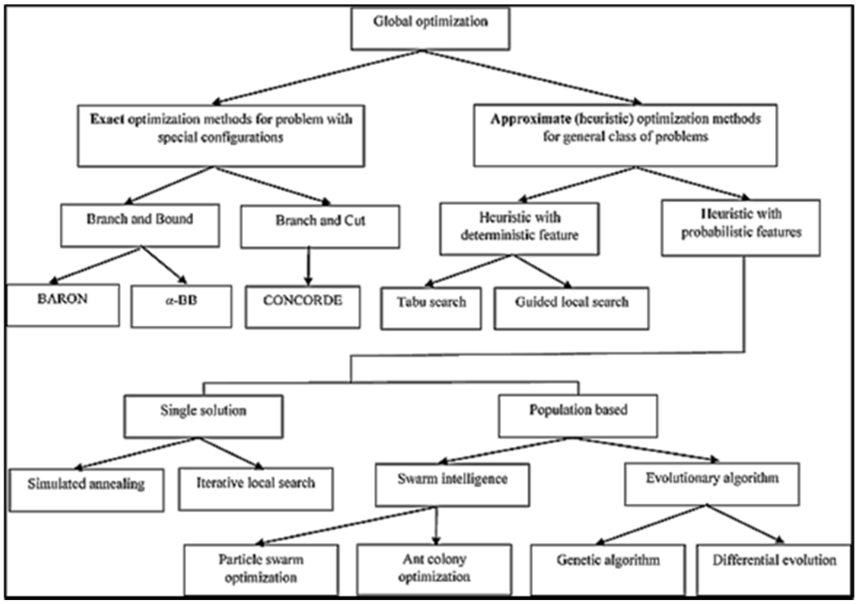

Figure2. FANET Optimization Techniques

B. *Whale Optimization Algorithm (WOA)*

The WOA is a novel optimization strategy that takes cues from humpback whales' methodical approach to hunting. Whales are intelligent and empathetic animals that can thrive alone or in groups because of their spindle cells. The larger humpback whale is the size of a school bus and feeds on krill and small fish. The humpback whales hunting process is known as bubble net feeding, and it may be scientifically explained to do optimization [25].

1) *Encircling Prey:* Humpback whales can pinpoint their precise locations to successfully capture their prey. It is assumed in WOA that the current best solution (search agent) signifies the intended prey and that the placements of other search agents may be altered to get the optimum solution. Equations (1) and (2) illustrate the activities.

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

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

Where$\vec{X}$p=prey position vector, t=present iteration, $\vec{A}$, $\vec{D}$ =distance between prey and position of whale, and $\vec{X}$ =Whale position vector, $\vec{C}$ are coefficient vectors considered by utilizing equations (3) and (4).

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

$$\vec{C} = 2.\vec{r}_{12\ldots}(4)$$

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) *Bubble Net Feeding Mechanism (Exploitation State)*

It defines two methods as follows:

a) The value of a is decreased in the shrinking encircling method. The variation variety of A is likewise scaled down by a to get the value in the range [-a, a]. Presumptuous values of A in [-1, 1], anywhere between the agent's actual position and the location of the best agent may be an acceptable explanation for the whale's new position.

b) Spiral adapting location: Originally it assesses the location of prey ($\vec{X}*$, $\vec{Y}*$) and whale ($\vec{X}$, $\vec{Y}$). This spiral equation (5) between the humpback whale and its prey's position is an approximation of the humpback's helical wrought motion.

$$\vec{X}(t+1) = \vec{D}^t . e^{bt} \cos(2\Pi t) + \vec{X}^*(t) \quad ...(5)$$

Here $\vec{D}^t = |\vec{X}^*(t) - \vec{X}(t)|$ which signifies the distance between the I_{th} whale and its current best prey, b=constant for understanding the logarithmic spiral structure, and t=any value in the range [1, 1]. Humpback whales revolve in a prey area inside a finch circle and alongside a spiral-shaped route at the same time.

As a result, we hypothesized that whales change their places throughout optimization with a 50% chance of selecting finch circular or spiral model Equation (6).

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A}.\vec{D} & p < 0.5 \\ \vec{D}^t . e^{bt} \cos(2\Pi t) + \vec{X}^*(t) & p \geq 0.5 \end{cases} \quad ...(6)$$

Here p=arbitrary number in [0, 1]. The following is an arbitrary method for searching for prey among humpback whales:

3) Prey Exploration

Whales employ random exploration to find each other's positions, while A is used to explore the prey. As a result, A is used for exploration (with arbitrary values 1 &>1), and | A| > 1 is utilized for global search Equations (7) and (8).

$$\vec{D} = |\vec{C}.\vec{X}_{rand} - \vec{X}| \ldots (7)$$

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

Here $\vec{X}_{rand}$=arbitrary location vector (arbitrary whale). The WOA starts with a collection of random solutions. When the process is repeated, the "whales" (search agents) rearrange themselves to follow the most optimum whale or a randomly chosen one. The input parameters such as P^w = Whales population, N^i = several iterations, and N^w= several whales and output optimal whale (drone) (X^*) are shown in the WOA algorithm.

Algorithm1. 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) Xi (i= 1,2, 3,………, Ni)	
4) Given initial values of a, A, I, c, p & N^i	
5) Calculate the fitness of all whales	$Ni *P*$
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 (|A|<1)	$N^i * N^w$
11) Modify the location of present whale (search agent) (eq. (1)(2)(3) & (4)	
12) Else if (|A|<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<0.5)	$N^i * N^w$
17) Modify the location of present whale (search agent) (eq. (5))	$N^i * N^w$
18) END IF	$N^i * N^w$
19) END FOR	$N^i * N^w$
20) Calculate the fitness of all whales	
21) Modify X* if there exists a better location	
22) it = it +1	
23) Modify a, A, I, c, & p	
24) END WHILE	

25) END WHILE

$N^i * N^w$

26) Return X*

$N^i * N^w$

N^i

27) STOP

N^i

N^i

C. Grey Wolf Optimization Algorithm (GWO)

It is becoming increasingly common to use algorithms in engineering applications due to their many advantages, including (i) being based on simple theories and being easy to the device, (ii) not requiring gradient information, (iii) being able to bypass local optima, and (iv) applying to an extensive variety of problems in many different fields. For various combinatorial optimization issues, a large variety of algorithms are introduced. One of the new methods is Grey Wolf optimization. This algorithm takes its cues from the social behavior of grey wolves, specifically the way they organize themselves into a hunting hierarchy. Grey wolves are the highest-ranking predators, and they reside in packs of 5–12 wolves. Grey wolves are divided into four groups based on their hunting strategy: alpha, beta, delta, and omega. The bundle's leader is an alpha wolf. This wolf has the authority to make decisions about where to sleep, hunt, and other matters. These wolves are known as dominating wolves because they demand that other wolves obey their commands [26].

1) *Leadership Hierarchy of Grey Wolf Optimization:* The grey wolf has the intrinsic ability to choose an alpha wolf to lead the pack during a hunt. Alpha, beta, and delta wolves may all go on a hunt together. Gray wolves frequently search by alpha, beta, and delta positions. Each grey wolf of prey is assigned a score based on its suitability and location. The pack is now hunting prey as a result of these better options. During iteration for the next feasible place, the movement of each grey wolf is saved. This social hierarchy is focused on the GW-COOP protocol's use of collaborative diversity. Fig.3 depicts the leadership hierarchy of GWO as shown below Fig.3.

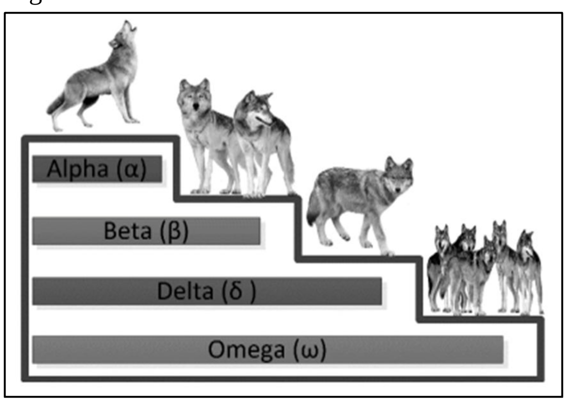

Figure3. Leadership hierarchy of GWO

Grey wolves prefer to be part of a pack. Their pack size averages 512 individuals, and they have a fairly tight social dominating structure. The alpha (α) wolves are the pack's leaders, and their decisions are based on the pack's wishes. The grey wolf hierarchy is divided into two levels: beta (β) and alpha (α). They're secondary wolves who help the alpha with various tasks or decisions.

They might be male or female as well. If one of the alpha wolves dies or reaches the age where he or she is no longer capable of performing well, beta wolves are the most likely candidates to take his or her place. The Beta wolf is in charge of leading the lower-level wolves. Delta (δ) occupies the third position in the grey wolf social order. Delta wolves are submissive to alphas and betas, but they exercise power over the lowest-ranking omegas (ω). The herd relies on the scouts to monitor the perimeter of the area and report any threats to the rest of the group. Elders are wolves who have served as alpha or beta in the past and have a lot of experience in the pack. The hunter aids the alpha and beta by capturing the game and preparing meals for the pack. Omega(ω) is the lowest rung in the grey wolf hierarchy. They're being held up as a scapegoat since they're the last wolves with access to food. All other dominant wolves must submit to them [27]. The omega wolf's actions contribute to completing the pack and maintaining the dominant structure, even if the omega coyote is not a significant member of the group. Omega has been reported to cause internal strife and issues throughout the entire package [28].

2) *GWO System Model:* Nodes in this network are not fixed to the ground but instead are free to move about and eventually settle in a particular spot. As can be seen in Fig.4 & Fig.5, the nodes communicate with their intended recipient using the grey wolf principles.

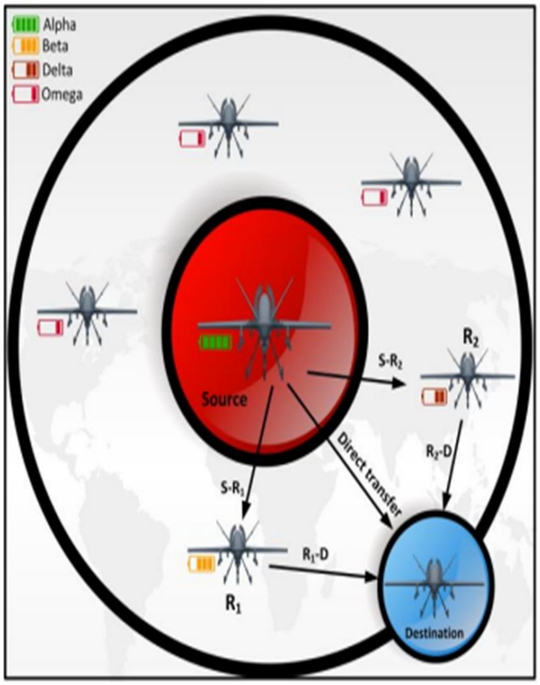

Figure4. GWO system model

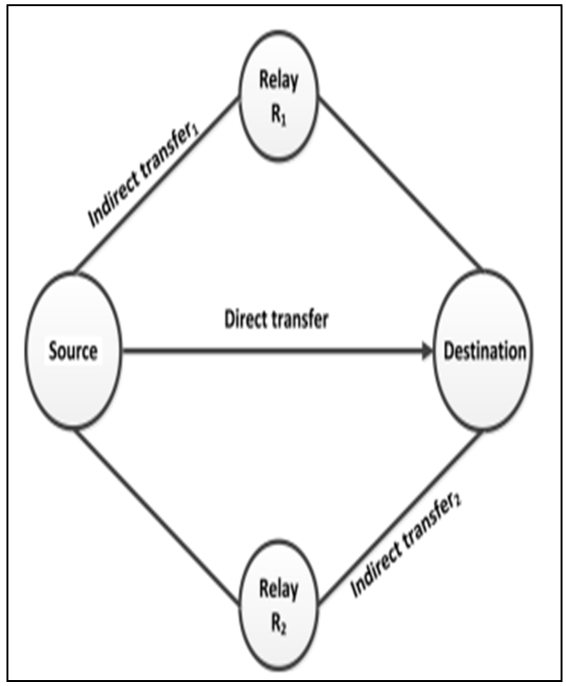

Figure5.Two relays model in GWO

Alpha is the finest possible network choice and is sometimes referred to as the source since it is just one node away from its final resting place. Beta and delta, represented by R 1 and R 2, are the second and third-best alternatives. The remainder of the network nodes, which are part of the contributor's catalyst, are presumed to be omega.

Algorithm GWO
Initialize the Grey Wolf population and algorithm parameters
Evaluate the fitness of each search agent Fit_j
Initialize the first best solution as X_α
Second best solution as $X_\beta$and
Third best solution as X_δ
While (k< maximum number of iteration or stop criteria obtained)
For i= 1; n
Update the current search agent position
End for
Evaluate the fitness fit;
Update the coefficient vector α, A and C
If any better solution, then update the best agent X_α X_β X_δ
K= k+1
End while
Stop the process and visualize the first best agent X found so far

The two-relay concept is used to route FANETs, which eliminates the instability of the links between nodes. This permits at least one path to the destination to be maintained. In FANETs, flying node stability and control are difficult to achieve. During the self-healing organization of dynamic networks, however, the GWO protocol assures network connectivity. This cooperative arrangement addresses the dynamic nature of networks in which each node has a role to play in routing.

D. Genetic Algorithm

Evolutionary or genetic algorithms are another name for genetic algorithms. Genetic algorithms are probabilistic in that they extract the optimization model into a parameterized coding form, layout the fitness function concerning the actual problem, determine the fitness value of each person in the population, and then obtain the next-generation population via selection, crossover, and mutation processes to find the optimal global solution. To choose features using a genetic algorithm, several iterations are necessary. If the learning technique is an iterative process, where the learning algorithm is used in each iteration to assess the fitness of each individual, the overall computational cost of the process will be quite high.

Genetic algorithm is established on "survival of fittest" theory of Charles Darwin. GA is a technique which efficient for optimization problem. It contains four types of operations:

1) Coding
2) Selection
3) Crossover
4) Mutation

In the area of artificial intelligence (AI) a GA is an analytical algorithm that imitates the process of natural selection. This is also called the metaheuristic. GA has some advantage such as solve the complex problem with no. of outputs and it is a technique which is very easy to grasp and it doesn't demand the mathematical terms [23].

E. ACO Algorithm

The ant colony optimization (ACO) was firstly proposed by Marco Dorigo in 1991. ACO is the technique for finding the shortest paths or routes between source to destination, each ant's effort to search a path or route between its nest and a food source. In real world where ants are wander randomly and able to search the shortest path or route between its nest and a food source, when the ants realized that the old path is not best way then they try to find the new shortest path and deposit a certain amount of pheromone trail, other ants follow the path where good amount of pheromone, and this path get more reinforced with more pheromone. The ACO is a stochastic method for resolving arithmetic issues that may be fundamental to discovering optimal pathways in graphs.

In this context, "artificial ants" refers to multi-agent approaches that are modeled after the activities of actual ants.

For optimal performance of wireless networks, the ACO method is often used to resolve a set of combinatory optimization challenges. Numerous case studies show that ACO-based routing algorithms improve network performance over other types of routing algorithms [28]. There is a hybrid feature selection method that combines ACO and GA. There is no local search option in GA, but there is an ACO, and this is a significant benefit. In contrast, GA operates on the whole population from the get-go, to take a global viewpoint [19].

The optimization algorithm of ACO

1) Activate the population (robotic ants) and the network nodes (source and destination).
2) Select next path(edge) arbitrarily according to the attractiveness (τ) and visibility(η).
3) Rand (choose available edge e):

$$= \frac{\tau(e) * \eta(e)}{\sum_{available\ edges\ e} * \tau(e)^t * \eta(e')}$$

4) Each ant keeps track, in a memory (tabu list), of the current state of its active executions.
5) Adjust the attractiveness of a path based on the traffic it receives from ants.

F. Particle Swarm Optimization (PSO)

The concept of PSO is given by Dr. James Kennedy and Dr. Eberhart in 1995. This algorithm inspired by the behavior of an organism like schooling of fish and flocking of birds in natural environment. This technique attempts to optimize a problem by continuously improved the particle solution. PSO has two basic operations first "velocity updating" and second one is "position updating". PSO is an optimization algorithm which provides initial population based on searching algorithm where each organism called particles change their position according to time. The main function of PSO is its ability to converge fast. It is based on an algorithm for swarm intelligence, which may be used too many different optimization problems. PSO is an optimization method that creates a starting population using a searching process in which each organism, or "particle," moves about over time. The particles in the PSO system are capable of interacting with their environment. Particles independently choose their spatial arrangement based on their own and their neighbors' prior knowledge.

For itself and its neighbor, particle found the best possible location. Thus, PSO is both a local and global search strategy [22].
The optimization algorithm of PSO

1) Initialization of particle: "organize a population of particle spread over R^N. Here R^N is N dimensional search space.
2) Calculate the fitness value: calculate each particle's position with the help of objective function.
3) Find the best position Pbest (P_i): if a particle's present position is better than the previous best position, upgrade the position.
4) Find the best position globally Gbest (P_g): the position of particle denoted as Gbest (according to particles best position).
5) Updating the velocity: particle i velocity represented by $V_i = (V_{i1}, V_{i2}, V_{i3}, V_{i4}.........V_{in})$.
6) The d^{th} $(1 \leq d \leq N)$ dimensional velocity Vid of each particle can be update using following equation:

$$V_{id} = w^* V_{id} + c_1^* r_1^*(P_{id} - X_{id}) + c_2^* r_2^*(P_{gd} - X_{gd})$$

Here, w is the inertia weight, c1 and c2 is constant whose value (0, 1), r_1 and r_2 is random function whose value (0, 1). Xid is the current dth dimensional position of particle 'i'.

7) Update the particle position:

$$X_{id} = X_{id} + V_{id}$$

8) Stop if criteria are satisfied otherwise goes to 'ii'.

III. PROPOSED TECHINUE

A. Hybrid of ACO-PSO Algorithm

To solving optimization problem, an original and knowledgeable algorithm called Swarm Intelligence (SI). The ACO and PSO are the two most successful technique of the ideal swarm intelligence. Hybrid ACO and PSO is a strategy that combines ant colony with particle swarm optimization. In the provided technique, the PSO is utilized to improve the ACO's qualities; this means that parameter selection is not based on simulated data but rather on a thorough scan of the PSO's particles. Additionally, we applied an enhanced ACO utilization technique to determine the ants' shortest journey or paths. We also made use of ACO to its fullest extent and uncovered the ants' shortest pathways using this method offers a critical advantage of local searching, not found in GA. On the other hand, GA considers a global perspective by operating on the complete population from the very beginning. Therefore, ACO and GA can nullify each other's drawbacks when hybridized. Using genetic algorithm to perform feature selection requires much iteration. If the learning algorithm is an iterative process, the computational cost of the whole process would be very expensive, since learning algorithm is used, in each iteration, to evaluate the fitness for each individual[29].

Like GA, PSO is also an evolutionary algorithm. Compared to GA, PSO does not need complex operators as crossover and mutation that GA does, it requires only primitive and simple mathematical operators, and is computationally inexpensive in terms of both memory and time [30]. Finally, choosing path pairs with the GA method shows the same path pairs, while the results of ACO and PSO methods are variative path pairs.

Algorithm of Hybrid ACO-PSO Technique:

1) First stage, to create the population of particle by using GA (Genetic Algorithm):
a) Initialization: produce initial population randomly.
b) Compute the energy efficient fitness value by using function, of each particle.
c) Use the particle processes of crossover, selection, and mutation.
d) The final energy aware cluster-based population will be produced.
e) End if the condition is contented otherwise go to 2.
f) The completed population would be introduced to a hybrid ACO-PSO.

2) Second stage, the hybrid ACO-PSO algorithm:

a) ACO:
- The final population is given by GA.
- Initialize metaheuristic information.
- Initialize the artificial pheromone.

- If stopping condition not satisfied do
- To set output
- Consider local path
- Updating Pheromone
- End if local best path better than global path than save local best path as global path.

b) PSO:

- Final population is obtaining from ACO with global path.
- Calculate the fitness value with the help of objective function.
- if a particle's present position is better than the previous best position, upgrade the position and consider this upgraded position as G-best (global position)
- Updating the Energy level and particle position.
- Stop, if final population is obtained otherwise go to b.

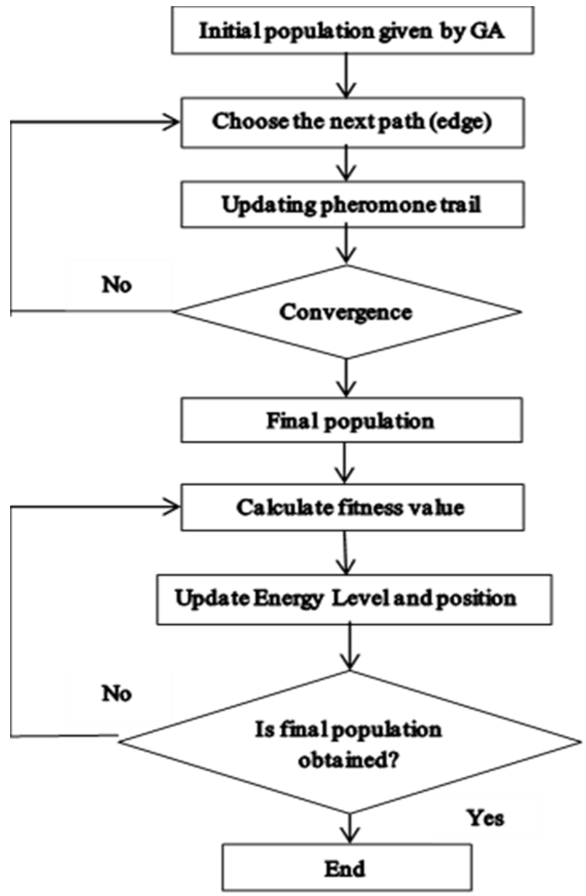

Figure6. Flowchart of hybrid ACO-PSO

IV. SIMULATION RESULTS AND PERFORMANCE ANALYSIS

A. Simulation Platform

NS-2 is the name of the simulator that operates at the application layer. The NS-2 front-end is an OTcl interpreter, whereas the backend is made up of C++ libraries. NS-2 is capable of simulating both wired and wireless networks, in addition to a broad range of communication protocols, such as multicast routing, UDP, and TCP, amongst others. In addition, NS-2 can simulate both wired and wireless networks simultaneously. The simulation parameter that would be explained further down would be displayed in Table.1 & Table.2.

Table1. Simulation parameters

Simulation Parameters	Values
Simulator Version	Ns-2.35 (Version)
Channel Type	Wireless
Protocol	ACO, GWO, WOA, PROPOSED
Simulation Time	200 (s)
No. of nodes	0, 5, 10, 15, 20, 25, 30, 40, 45
No. of times path travel	0, 10, 15, 20, 25
Constant bit rate	100kb

Table2. Simulation parameter

ACO parameters		PSO parameters	
Parameters	Value	Parameters	Value
Number of ants	Features number in the database	Swarm size	Features number in the database
Number of nodes	Features number in the database	W	0.6571
α	1	C1	1.6319
β	5	C2	0.6239

B. Result and Analysis

1) End-to-End Delay

FANET's affiliation and capability are best characterized via EED, which is a hybrid of route discovery and communication time. For optimal routing, the minimum value of EED is chosen. The WOA yields the lowest EED value for 1000m^2 area (0.2914), whereas the ACO yields the lowest value (-1.3) and the GWO yields the lower value (0.2), proposed hybrid ACO PSO yields (1.2) as shown in Fig.7 & Fig.8 shows EED variations for different data rates for proposed hybrid ACO PSO.

The value of EED increases as the network area grows because data is transmitted across a greater distance in a bigger network area. Table.3 depicts end-to-end delay with various data rates at various speeds as shown below.

Table3. End-to-End Delay (%) with various Data Rates(packets/sec) at various Speeds(m/sec)

Speed (m/sec)	Data Rate (packets/sec)					
	4	6	8	10	12	14
1	1	3	3	3	6	4
1.5	1	3.55	3	3	6	4.5
2	1	4	3	3	6	5
2.5	1.2	4	4	3	7.5	5
3	1.4	4	5	3	9	5
3.5	1.85	4.5	5	3.5	9.5	7
4	2.15	5	5	4	10	8
4.5	2.55	6	5.5	6	10	9.3
5	2.9	7	6	8	10	10

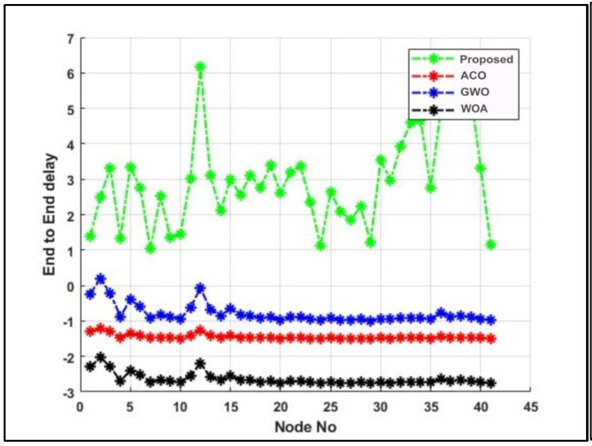

Figure7. End to End Delay

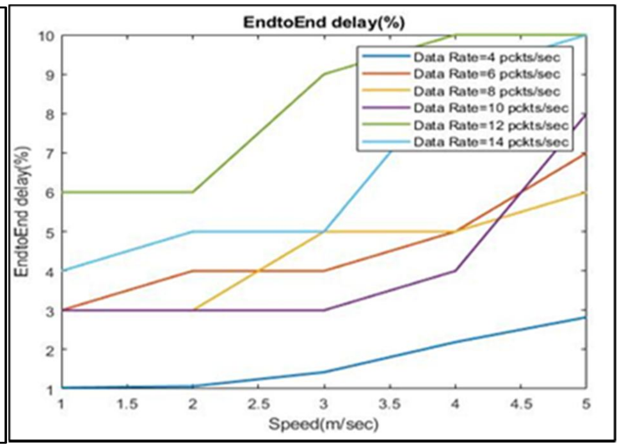

Figure8. End to End Delay with Data Rate

If transmission varieties are enlarged, the value of EED decreases since fewer drones are required for data transfer. The value of EED increases when the velocity ranges are expanded since having a maximum velocity of drones is required for sending data.

2) Packet Delivery Ratio (PDR)

This value is based on the proportion of data packets sent that were successfully received at their intended destination. The final cost is calculated as a proportion of the total packets sent. PDR in FANET is the proportion of data sent by optimum drones using WOA that reaches the base station.

$$PDR^t = \frac{Data_{BS}^t}{\sum_{i\in O_d}\sum_{j\in N_{di}} Data_j^t}$$

Where O_d=group of optimal drones, $Data^t_{BS}$=sending data arrived to the base station (time t), N_{di} =group of all drones in i^{th} optimal drone, and PDR^t=PDR (time t), &$Data^t_j$ =data transmitted by j^{th} drone to the base station (time t) using proposed hybrid ACOPSO over other FANET routing techniques.

Table4. Packet Delivery ratio with Data rate and number of paths

Data rate	Number of paths					
	4	6	8	10	12	14
5	0.15	0.2	0.35	0.45	0.52	0.6
10	0.4	0.51	0.75	0.92	1.12	1.38
15	0.5	0.85	1.11	1.42	1.6	1.94
20	0.98	1.49	1.97	2.48	2.94	3.42

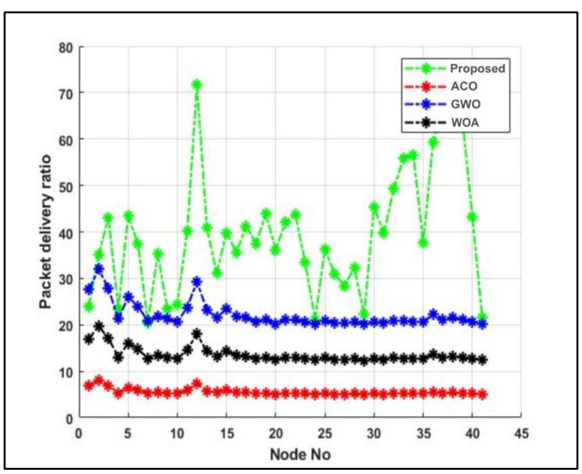

Figure9. Packet Delivery Ratio

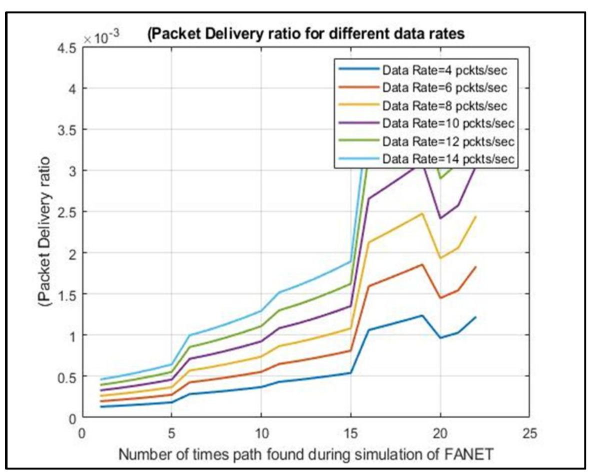

Figure10. Packet Ratio with Data Rates

In FANET, Fig.9 reveals that the Proposed hybrid ACOPSO generates a maximum PDR value of 70% for 1000 m * 1000 m, GWO generates PDR value of 32% and WOA generates a maximum PDR value of 20%, while ACO generates a maximum PDR value of 11%. The number of times packets are detected during FANET simulation in PDR for hybrid ACOPSO is shown in Fig.10. & Table4 demonstrates the packet delivery ratio with data rate and several paths traversed during simulation.

3) Throughput

In a network, this parameter describes the rate of data transfer between two nodes. All drones transmit data through WOA, ACO, and GWO via FANET, with the sent data per unit time slice arriving at the base station. The value of throughput decreases because data is transmitted across a greater distance, reducing the chance of delivery over a bigger network area when the network region is expanded. By using energy aware clustering approach Fig.11, the proposed hybrid ACOPSO performs better, the value of throughput increases because the number of drones required to send data is reduced when transmission ranges are extended, boosting the likelihood of packet delivery. Having an extreme velocity of drones to demand conveying data reduces the probability of packet delivery, therefore the value of throughput drops as the velocity varieties are improved. The network lifetime plot for different data rates during the simulation of proposed hybrid ACOPSO technique shown below in Fig.12 & Table5 demonstrates the throughput with a different data rates.

Table5. Throughput (MBps) with different data rate

Number of times path found during simulation (m/sec)	Data Rate (packets/sec)					
	4	6	8	10	12	14
5	0.4	0.58	0.83	0.97	1.18	1.4
10	0.29	0.34	0.47	0.54	0.66	0.78
15	0.23	0.25	0.38	0.42	0.5	0.59
20	0.19	0.2	0.32	0.38	0.41	0.46

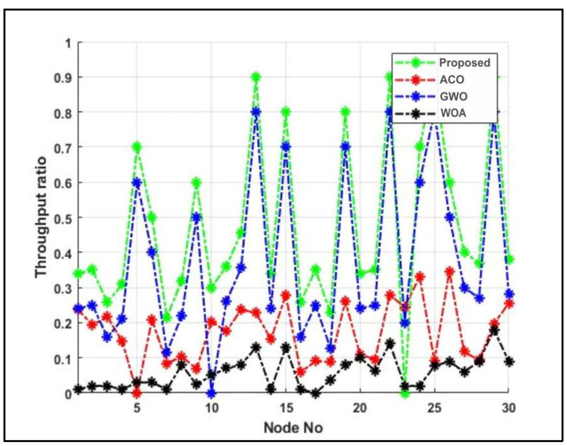

Figure11. Number of nodes vs throughput ratio

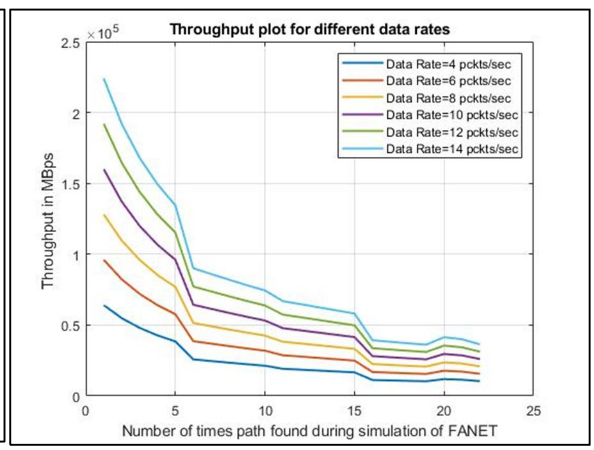

Figure 12. Throughput Variable Data Rates

4) Total Energy Consumption

The total energy consumption is the energy consumed by the algorithm for the whole network. There are three main mechanisms which consume energy in drones: energy needed to operate drone, energy consumed by the sensors mounted on the drone, and energy consumed in communication which is also the main source of energy consumption. From Fig.13, it can be seen that increasing the number of drones in the network consumes more energy. From the results, it is clear that our proposed hybrid ACOPSO technique performs better as compared with the other three clustering schemes.

Lower energy consumption of our proposed scheme is because of the energy aware CH selection and cluster management. It can be noted that the average energy consumption of Proposed hybrid technique has improved 23%,33% and 42%when compared with that of GWO, ACO and WOA, respectively.

C. Comparison Analysis

A graphical illustration of the comparison of throughput for WOA, GWO, ACO, and the suggested hybrid ACOPSO technique can be seen in Fig.14. In the beginning, the throughput of the WOA method is higher when compared to the ACO at node 5, but the throughput of the GWO method is much higher when compared to both the WOA method and the ACO method at node 30. It is evident from the graph of comparison that the throughput of our suggested technique considerably and significantly increases at various numbers of nodes from early to end stages as compared to other ways. The comparison among optimization algorithms WOA, GWO, ACO, and the suggested hybrid ACOPSO where, in hybrid ACOPSO parameter doesn't depends on artificial experience, but relies on the robust search on the particles by the PSO. Idea behind to use Genetic Algorithm is to enhance the attributes in the ACO, which defines that the selection for energy efficient best clustering routing algorithm.

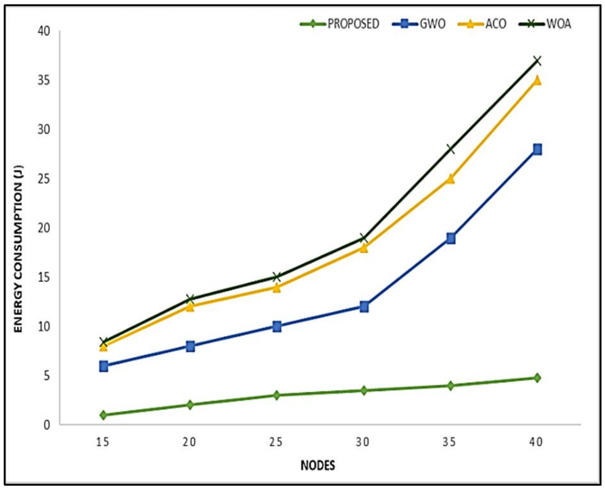

Figure 13. Energy Consumption

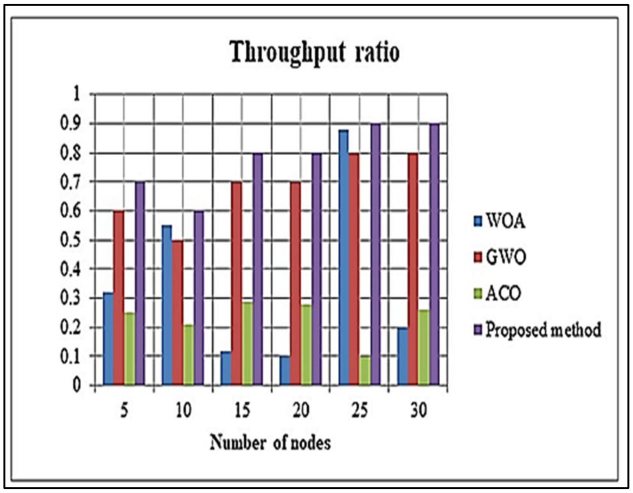

Figure14. Throughput Comparison

We also used an enhance utilization of ACO, by this technique we have found the shortest path or routes of ants. The output of the experiment show that the optimize algorithm not only reduce the number of paths in the ACO. But also finding the shortest energy efficient best path at the place of largest path. The given hybrid algorithm is proved to be efficient than PSO and ACO. Two test functions are also used to prove the efficiency of hybrid ACOPSO. By using this new hybrid ACOPSO algorithm the disadvantage of both the algorithm has been reduced.

V. CONCLUSION AND FUTURE WORK

This study utilizes the evolutionary algorithm and cooperative diversity to provide a better routing protocol for FANETs that can adapt to connection and loss scenarios. Energy consumption is used to estimate the number of packets received in the base station. The more energy usage is steady; the more packets are received at the base station. This improvement is due to the CH selection, which guarantees that all clusters are balanced. This equilibrium stabilizes CH selection, resulting in consistent energy loss. The computed performance demonstrates that proposed hybrid ACOPSO technique outperforms WOA, GWO, and ACO on several factors, including a PDR, end-to-end latency, energy consumption, time complexity, and throughput.PSO is used to better the features of the ACO, qualities which require that parameter selection is not based on simulated experience but rather on a comprehensive examination of the particles that make up the PSO. From the comparative analysis, it is concluded that our proposed method is having achievable throughput which significantly increases as compared to other methods. For applications needing frequent UAV communications, the suggested techniques should be stable and long-lived in the future. In the future research studies, the authors can be focused on performance in small scale and peripheral sizes, and they can use the machine learning and deep learning for routing and then for load balancing by using the metaheuristic algorithms.

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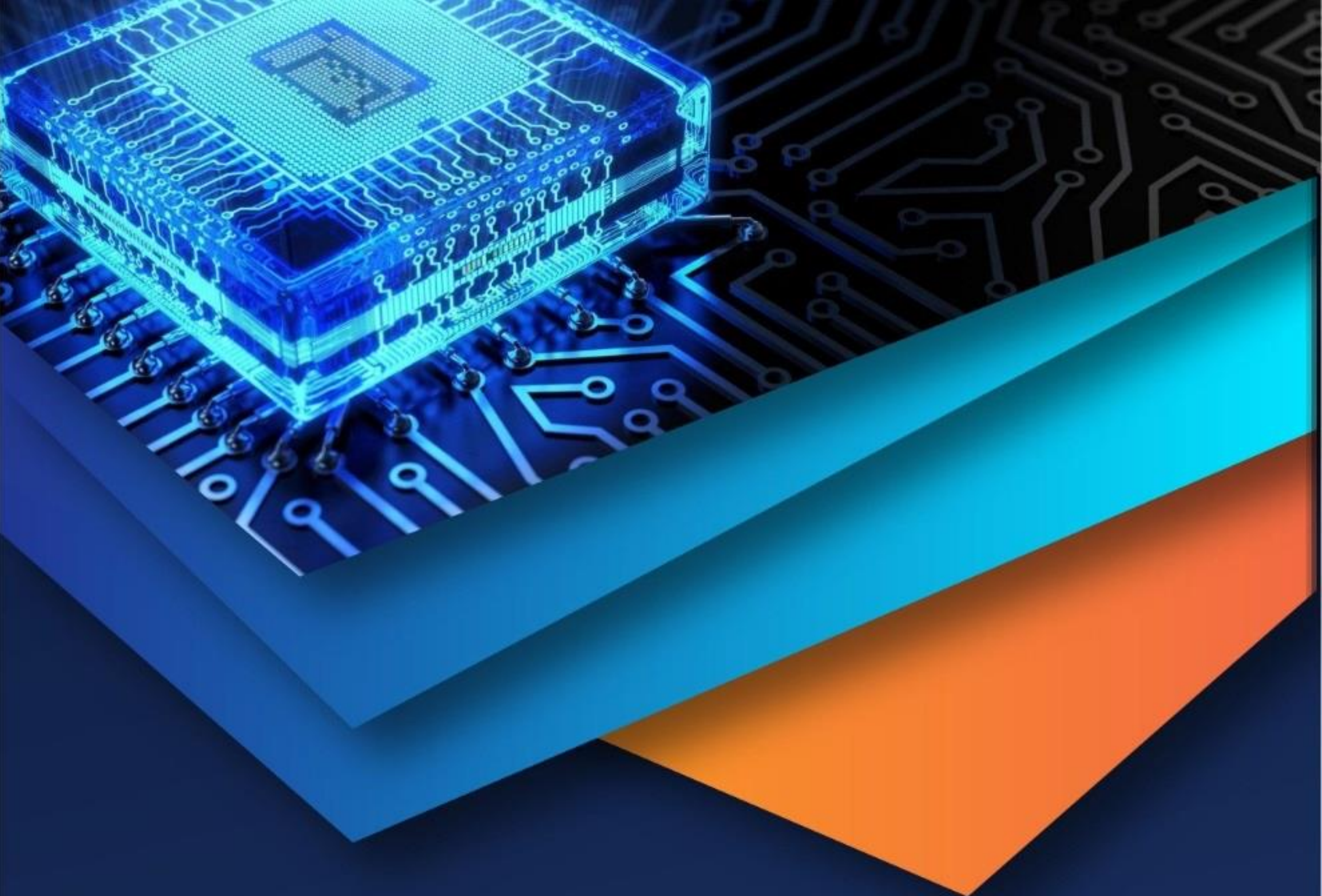

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