Research Article

Dynamic Routing and Coordination of Cluster for Unmanned Aerial Vehicle (UAV) Swarms

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The flying networks provide an efficient solution for a wide range of military and commercial purposes. The demand for portable and flexible communication is directed towards a quick growth in interaction among unmanned aerial vehicles (UAVs). Due to the frequent change in topology and high mobility of vehicles, routing and coordination becomes a challenging task. To maximize the throughput of the network, this study addresses the UAV swarm's problems related to the coordination and routing and defines the proposed solution to solve these issues. For this, a network is assumed which contains an equal number of dynamic vehicles. It also presents the communication graph concept of UAVs and designs a fixed-wing UAV model to improve the efficiency of the network in terms of throughput. Furthermore, the proposed algorithm based on Cauchy particle swarm optimization (CPSO) aims towards the better performance of UAV swarms and aims to solve the combinatorial problem. The simulation results show and confirm the performance of the proposed algorithm.

1. Introduction

In recent years, unmanned aerial vehicles (UAVs) have gained interest and have been applied in the area of search and rescue, agriculture defence, transportation, monitoring, and surveillance [1]. These vehicles can cover wider areas in the field. The coordination and monitoring system is needed for the fleet to determine their route and utilize this resource in a very efficient manner [2]. The UAV technology is also known as utilizing a network of UAVs. It attains sensing and actuating equipment to collectively perform the complicated task. Cooperation and coordination between the networks of UAV swarms will help to complete complicated missions across a large area. The decision making for the next position occurs at many stages of communication. Mostly many vehicles communicate via air to ground or air to air along with their control stations [3–5]. This technology also provides flexible configuration, improvement in the communication performance, and line-of-sight communication link on demand. Many studies show and provide a flexible solution for routing problems. A hierarchical structure is

considered to have a UAV cluster. With the help of the proposed algorithm, routing takes place within the cluster and it is a basic tool for cluster communication [6]. Some other methods are used to improve the throughput of a channel by which UAV's applications expand vastly but still issues are present [7]. The UAV network information sharing is a more challenging problem limited to the throughput especially in disaster areas. It affects the overall effectiveness of the operation. For UAV swarms, different methods and techniques are designed for an optimal solution. By using these techniques, capacity of a channel is improved with an increase in the rate of the spatial multiplex.

With the development of technology, the spectrum deployment and communication ratio is highlighted. Previously, many scientists tried to solve the UAV swarm problem with different technologies, but still there are some issues to be solved. Many researchers had studied the cellular network of UAVs [8, 9]. It is required to centralize the control due to the high intelligence level of unmanned vehicles. To address the need of UAV's network information

distribution necessities, the challenges shall be added especially in distributed scenarios that affect the overall operation [10]. So, the effective techniques are specifically designed for UAV swarms. Cauchy particle swarm optimization (CPSO) has an effective result bearing key factors enhancing effectiveness that are topology structure, parameter selection, and swarm initialization [11, 12]. But in PSO, the disadvantage is that it easily falls into local optimum. Therefore, algorithm CPSO attains the best solution in minimum time. The operators help in reducing the possibility of immature convergence by dealing with every ant individually.

In [13], the study provides the solution for the routing problem of the vehicle. The problem is split into a set called a cluster. This study finds the best possible distance of the route of the vehicle. The PSO technique is adopted to solve the routing issues. In [14], the improved version of PSO is called combinatorial particle swarm optimization which is used to find the number of clusters. It also increases the population variety and eliminates terminated particles. It also increases the speed of junction and solution's quality. In another study, a CPSO technique is used [15]. On the other hand, the inertia weight factor and chaotic maps are introduced to solve the clustering optimization. This study combines CPSO with weight factor and chaotic maps to attain better performance. In [16], clustering particle swarm optimization (CPSO) is proposed for the efficiency of search. This algorithm cannot guarantee convergence due to the sensitivity of the original cluster. The CPSO algorithm finds the best possible solution. Similarly, in another study [17], topology-based routing protocols improve the adeptness of the system. It also focuses on a detailed review of routing protocols that are topology-based. Furthermore, simulation evaluates the topology-based routing protocols. In [18], particle swarm optimization (PSO) with software-defined networking-based communication protocol is proposed which guarantees network management. Novel particle selection criteria are proposed for coordination purposes, which aims to guarantee network manageability of UAV formations, thus being able to guarantee service persistence in case of node failure occurrence. In [19], the article presents a review on the major research areas of unmanned vehicles, i.e., 3-degree-of-freedom (3DOF) routing algorithm and routing protocols. This article also aimed to provide a comparison between the methods and algorithms to find the best ones among these algorithms for a particular application. On the other hand, in a dynamic environment, the stability of topology is presented. The algorithm used in that article is the cluster routing algorithm used for the stability of topology and proper transmission. The proposed algorithm in [20] is paralleled with ant colony optimization (ACO) and particle swarm optimization (PSO). In [21], a new method has been proposed due to a change in the topology of a network. A dynamic routing method for a group of UAVs using SDN technology with dynamic topology was proposed. Simulation results show the comparison of the proposed method's performance with other algorithms. The simulation results show that the proposed method has better results than traditional algorithms. All

these aforementioned studies use different algorithms and methods to solve the issue. But still there are issues in the topology structure, swarm initialization, and parameter selection in every algorithm. Our proposed CPSO shows effective results in solving all these issues. The only disadvantage of using PSO separately is that it falls into local optimum. So, the proposed algorithm is the best choice to solve the problem with minimum time.

Our contributions target the design of a CPSO algorithm for the better performance of UAV swarms. In this study, a swarm communication model along with a network mobility model is presented. Similarly, the fixed-wing UAV model is also presented with a communication graph concept of UAV. This article also offers the problem of UAV's swarms to maximize the throughput of the network. The network modelled is composed of multiple UAVs to form dynamic routing topologies. The advantage of the algorithm is that it improves overall fitness. Lastly, the MATLAB simulations verify the reliability, performance, and fitness of the CPSO.

This paper is organized as follows. The introduction is presented in Section 1. The state of the art is given in Section 2. The problem statement and its proposed solution are given in Section 3. Section 4 gives the preliminaries of UAV communication and its routing mobility model. In Section 5, the proposed solution is presented. The simulations are given in Section 6. Section 7 presents the conclusion of this paper.

2. State of the Art

A dynamic routing protocol is projected in [22] for safe and consistent transmission. The algorithm proposed in the study works on two phases that are security and routing. It finds the path which is cost-effective among the source and destination node and focuses on the security of transmitted data. In [23], a geographic position-based routing protocol for UAV networks is proposed. This is used for the dejected protocols and position-based protocols. As compared with the hop by hop routing protocols, this method fully utilizes the transmission opportunities of all the links. Similarly, in [24], UAV swarm network is proposed and the optimal number of vehicles is analysed. Moreover, a low-latency routing algorithm is designed based on the connectivity of the network and partial location information. The results verified the proposed algorithm which decreases the link average and improves the packet delivery ratio.

Likewise, in [25], a very cheap adaptive routing protocol is proposed which exploits learning algorithm and topology features for UAV swarm. This algorithm represents the most suitable parts of swarm formation which are geometric addressing module, leaf-like routing pipe, and low-complexity learning model. In [23], OLSR algorithm is proposed in terms of delay, throughput, and the load of the network. This routing protocol depends upon the link-state algorithm. Furthermore, the performance of the protocol is examined and analysed under different scenarios. The simulation results show that the link-state routing protocol has improved key indicators. Lastly, in [26], a dynamic UAV positioning method is proposed to maximize the value of sensors

attained from multiple UAVs. To support real-time sensor data monitoring, the data should be delivered to the ground base station using an ad hoc network. In this article, particle swarm optimization is used to derive the optimum UAV location.

3. Problem Statement and Its Solution

3.1. Problem Definition. This section defines the problem statement and the proposed solution. Considering a given scenario having three clusters may vary according to the requirement of the task. Each of them contains an equal number of UAVs having a cluster head (CH). Accordingly, every vehicle is required to be located at different positions or stations by communicating with each other through coordination among them. Swarms are assigned with an independent motion to form a dynamic topology. When routing and coordination of swarms takes place, the intersection points remain unchanged. The development of the flight or plan takes a little bit of time even if the inputs change concerning time. The flow comprises three steps which are as follows. (1) Start-CH, (2) CH-Another CH, (3) Another CH-End. Figure 1 shows these parts in black, red, and green colours, respectively. UAV attains flight time which is equal to the sum of the time consumed in transition between the base of fleet and interest points and elapsed time during the execution of the task at interest points. During the flight, UAV needs to share the information which is a problem to the throughput in the network.

3.2. Proposed Solution. The aforementioned problems are solved by using our proposed algorithm based on CPSO in this study. It creates an efficient strategy by fixing the parameters and different variables to reflect the current situation. It aims towards the better performance of UAV's swarms and to solve the combinatorial problem. This solution is feasible for choosing the proper cluster head and for the problem of the group of routes that may arise when the number of vehicles increases. Each route starts and ends at a

station that is chosen among all available stations without overhead of the allowed time for the flight.

4. Preliminaries of UAV Communication and Its Routing Mobility Model

4.1. Graph Theory Concept of UAV. Assume that $G(t) = \{V(t), E(t), W(t)\}$ is a directed graph when drones are flying in a formation [27], where $V(t) = \{V_1, \dots, V_n\}$ is called the vertex set, $E(t)$ is called the edge set, and $W(t)$ is called the weight adjacency matrix. The directed graph edge is denoted by $e_{ab} = (V_a, V_b)$, where V_a is the tail of the edge and V_b is the head of the edge. The weight adjacency matrix $W(t) = [w_{ab}]$, whereas the matrix elements show the adjacency weight. The communication node a gets information from b node when $w_{ab} > 0$. The diagonal matrix is represented by $D = \text{diag}\{d_a \mid a = 1, \dots, n\}$ has elements of matrix $W(t)$ get added to attain d_a . Laplace matrix of graph $G(t)$ is defined as $L = D - W(t)$, where $G(t)$ is an undirected graph when $w_{ab} = w_{ba}$. The undirected graph is defined as if two nodes in the graph are connected by the edges $G(t)$. The matrix L is diagonalized to its min value of matrix Z which satisfies

$$0 = \zeta_1 < \zeta_2 \leq \zeta_{\max}. \quad (1)$$

The eigenvalues of matrix L are $\zeta_1 \sim \zeta_{\max}$. The communication topology of UAVs consists of drones in an undirected connected graph. The second-order equation below defines the dynamic system model of UAVs.

$$\begin{cases} \dot{x}_a(t) = v_a(t), \\ \dot{v}_a(t) = c_a(t), \end{cases} \quad (2)$$

$\therefore a = 1, \dots, n,$

where $x_a(t)$ is defined as the position status, $v_a(t)$ is defined as the speed status, and $c_a(t)$ is the control input of member a . The following control protocol is espoused to make sure that the formation members are consistent with the expected movement status.

$$c_a(t) = \sum w_{ab} [n_1 (x_b(t-T) - x_a(t-T) + r_{ab}) + n_2 (v_b(t-T) - v_a(t-T))] + \sum_{s=1}^{n_3} h_a (v_s - v_a), \quad (3)$$

where the control gains of the system are n_1, n_2 , and n_3 . The time required for information to transfer from member b to a is denoted by T . r_{ab} is the relative position, and v_s is the expected speed. The ability index is denoted by h_a which is

used to attain the expected speed information of the formation. The aforementioned control protocol matrix is defined as

$$C(t) = -n_q(LX(t-T) - \text{diag}(WR)) - n_2LV(t-T) - n_3H(V(t) - V_s \otimes 1_{k \times 1}), \quad (4)$$

where $C(t) = [c_1(t), \dots, c_n(t)]^T$ is the vector formed by the formation members control input, x is comprised of position status of formation members

$X(t) = [x_1(t), \dots, x_n(t)]^T$, and the speed status vector is denoted by $V(t) = [v_1(t), \dots, v_n(t)]^T$. r_{pq} forms the matrix R . $\text{diag}(WR)$ is a vector of $W \times R$ diagonal elements.

Similarly, h_p forms a diagonal matrix H . The systems state equation can be written as

$$\begin{bmatrix} \dot{X} \\ \dot{V} \end{bmatrix} = \left(\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \otimes I_n - \begin{bmatrix} 0 & 0 \\ 0 & n_3 \end{bmatrix} \otimes H \right) \begin{bmatrix} X \\ V \end{bmatrix} - \left(\begin{bmatrix} 0 & 0 \\ n_1 & n_2 \end{bmatrix} \otimes L \right) \left[\begin{bmatrix} X(t-T) \\ V(t-T) \end{bmatrix} + \begin{bmatrix} 0 \\ n_1 \end{bmatrix} \otimes \text{diag}(WR) + \begin{bmatrix} 0 \\ n_3 v_s \end{bmatrix} \otimes (H \times I_{k \times 1}) \right]. \quad (5)$$

The control protocol of the above system is

$$\begin{cases} \lim_{t \rightarrow \infty} \|x_a(t) - x_b(t)\| \rightarrow r_{ab}, \\ \lim_{t \rightarrow \infty} \|v_a(t) - v_b(t)\| \rightarrow 0, \\ \lim_{t \rightarrow \infty} v_a(t) = \lim_{t \rightarrow \infty} v_b(t) \rightarrow v_s. \end{cases} \quad (6)$$

The speed of both members a and b reached the expected speed v_s . Similarly, the relative position of both members reached the expected position r_{ab} .

4.2. Swarm Communication and Mobility Model. Suppose a network of UAVs forms a swarm. A swarm includes a set of aerial vehicles that can fly together and perform complicated tasks with little changes in topology. Thus, routing and coordination of swarm takes place. Similarly, swarms form a dynamic topology due to the assignment of independent motion trajectories. So, for internal swarm communication, routing is used. The network structure has a human in loop and self-organization control with some other features [28, 29]. Furthermore, assume a control station (CS) that is answerable for providing communication to clusters. All vehicles are equipped with an antenna. A hierarchal structure network is designed. The proposed technique is implemented due to its high performance, high signal processing complexity, and so on. In the swarm communication framework, one tier is for inner and the other is for outer communication [30–32]. According to the requirement of the mission, the vehicles are divided into subgroups for swarms. The subgroup adopts aerial vehicle (AV) which is used for sharing intelligence. The structure of the cluster adopts a cluster head member (CHM). The information flow is defined in the problem statement with the help of a diagram. The communication process of swarms especially for inner and outer communication among the subgroups of swarms takes a little bit of time. Each vehicle operates in two types of mode: out of the band and in-band full-duplex. CS wirelessly communicates with AV and CHM in the same period. The swarm's communication is controlled by the clustering of CS assuming time-division mode activated by CS. Figure 2 shows the system model of swarms in which blue and green arrows show the frequencies. Similarly, orange lines show some interloping among the aerial vehicles.

4.3. Fixed-Wing UAV Model and Its Coordination. The point mass system is used to model fixed-wing UAVs [33]. Consider a swarm of UAVs given below:

$$\begin{aligned} \dot{x}_n &= V_n C \Gamma_n C Y_n, \\ \dot{y}_n &= V_n C \Gamma_n S Y_n, \\ \dot{o}_n &= V_n S \Gamma_n, \\ V_n &= \frac{\tau_n - d_n}{M_n} - g S \Gamma_n, \\ \dot{\Gamma}_n &= \frac{l_n S \phi_n - M_n g C \Gamma_n}{M_n V_n C \Gamma_n}, \\ \dot{Y}_n &= \frac{l_n S \phi_n}{M_n V_n C \Gamma_n}, \end{aligned} \quad (7)$$

where the forward displacement and horizontal displacement are denoted by x_n and y_n , respectively, $\dot{o}_n$ is the height, V_n is the ground velocity, Γ_n is the flying path angle, Y_n is the heading angle, and ϕ_n is the banking angle. Thrust is denoted by τ_n , d_n is the drag, lift is denoted by l_n , and the gravitational acceleration and mass are denoted by g and M_n , respectively. C and S denote sin and cos. The nonlinear model [34] by using feedback linearization can be linearized as

$$\begin{cases} \ddot{x}_n = c_{x_n}, \ddot{y}_n = c_{y_n}, \ddot{o}_n = c_{o_n}, \end{cases} \quad (8)$$

where the simulated control inputs are c_{x_n} , c_{y_n} , and c_{o_n} . The actual control inputs are thrust, lift, and banking angle which can be written as

$$\begin{aligned} \tau_n &= M_n [(c_{o_n} + g) S \Gamma_n + (c_{x_n} C Y_n + c_{y_n} S Y_n) C \Gamma_n] + d_n, \\ l_n &= \frac{M_n (c_{o_n} + g) C \Gamma_n - (c_{x_n} C Y_n + c_{y_n} S Y_n) S Y_n}{C \phi_n}, \\ \phi_n &= \tan^{-1} \left(\frac{c_{y_n} C Y_n - c_{x_n} S Y_n}{(c_{o_n} + g) C \Gamma_n - (c_{x_n} C Y_n + c_{y_n} S Y_n) S Y_n} \right). \end{aligned} \quad (9)$$

Furthermore, V_n , Y_n , and o_n must meet the parameters which are as follows:

FIGURE 1: Information flow from start to endpoint.

$$\begin{cases} V_{\min} \leq V_n \leq V_{\max}, \\ \Upsilon_n \leq \frac{\mu_{\max} g}{V_n}, \\ \zeta_{\min} \leq o_n \leq \zeta_{\max}, \end{cases} \quad (10)$$

where the minimum velocity and maximum velocity are denoted by $V_{\min}$ and $V_{\max}$. Maximum lateral overload is represented by $\mu_{\max}$. The minimum climbing speed and maximum climbing speed are denoted by $\zeta_{\min}$ and $\zeta_{\max}$. Two coordinate coefficients are introduced that must be added in every UAV as a function for its route to meet spatial and temporal constraints for the group. The function is expressed as

$$\begin{aligned} F_{C_n} &= F_{T_n} F_{S_n}, \\ F_{T_n} &= \begin{cases} \frac{J}{(t_1 - t_2)}, \\ 0, \end{cases} \\ F_{S_n} &= \begin{cases} d, \\ 0, \end{cases} \end{aligned} \quad (11)$$

where the coefficients of temporal and spatial coordinates are denoted by F_{T_n} and F_{S_n} , respectively. t_1 and t_2 represent the expected arrival time of UAVs and J is a constant. t may vary depending upon the number of vehicles.

5. Proposed Algorithm

5.1. Cauchy Particle Swarm Optimization (CPSO). This computation-based optimization is based on the study of natural behaviours. This technique provides random solutions and updates the velocity and position to attain the

universal best solution. Each unit updates the searching position with the help of its best outcome. The updated position of the unit depends upon the present velocity and past position. Now, the new position becomes the best individual position and it is superior to all other positions. The equation below becomes Cauchy distribution if w meets the condition in the equation

$$F(w, w_0, \delta) = \frac{1}{\pi} \left[\frac{\delta}{(w - w_0)^2 + \delta^2} \right], \quad (12)$$

whereas $w \in (-\infty, +\infty)$, the highest value of the function is denoted by w_0 , the width related to half of w_0 is δ . When w_0 and δ are 0 and 1, respectively, w meets the probability density function (PDF) and the above equation becomes

$$f(w, 0, 1) = \frac{1}{\pi} \tan^{-1} w + 0.5. \quad (13)$$

Map operators and compass operators are used to find the global best outcome during search problems in the PSO algorithm. Therefore, a particle's position and velocity are to be determined by the outcome. Cauchy operator K_1 increases the searching area and also avoids falling into local optimum. Operator K_1 can be written as

$$\begin{cases} \frac{1}{\pi} \tan^{-1} K_1 + 0.5, \\ K_1 = \tan[\pi(\text{rand} - 0.5)], \end{cases} \quad (14)$$

where rand is 0 or 1. The rule that updates each particle $\wp_n$ in every repetition is given as

$$\wp'_n = \wp_{(n0)} + K_1(\wp_{(n0)} - \wp_e^G), \quad (15)$$

where the calculated position of n particle is represented by $\wp_{(n0)}$. The best global position is $\wp_e^G$, and $\wp'_n$ is the position of n after an update. The position of n^{th} particle during the next repetition is given as

FIGURE 2: System model for UAV network consisting of three swarms.

$$\wp_n = \begin{cases} \wp'_n, F(\wp_{(n0)}) > F(\wp'_n), \\ \wp'_{n0}, F(\wp'_n) > F(\wp_{(n0)}), \end{cases} \quad (16)$$

where $\wp'_n$ will be far away from $\wp_e^G$ when K_1 is positive and vice versa. The most important advantage of using Cauchy operators is that particles scatter away from the center to find a better position. By equating updated position with earlier one, better fitness remains.

During the landmark operator phase, converging to the center of the swarm decreases swarm population. This problem is prevented by replacing the landmark operator with Cauchy which is used to update the particle based on its best position. The function of Cauchy is written as

$$f(w, 0, 1) = \frac{2}{\pi} \tan^{-1} w, \quad (17)$$

where $w \in (0, +\infty)$. Cauchy operator K_2 is written as

$$\begin{cases} \frac{2}{\pi} \tan^{-1} K_2 = \text{rand}, \\ K_2 = \tan\left[\frac{2}{\pi} \text{rand}\right]. \end{cases} \quad (18)$$

Each particle gets updated after each repetition according to the following rule:

$$\wp_{n0}^{\sigma_{\min}} = \wp_{n0}^{\sigma_{\max}} + K_2(\wp_e^G - \wp_{n0}^{\sigma_{\max}}), \quad (19)$$

where the position of n^{th} particle is $\wp_{n0}^{\sigma_{\max}}$. The best global position is given as $\wp_e^G$. Due to K_2 , each particle moves towards the best global outcome. This operator guarantees the steady convergence of the algorithm.

Consider planning in three-dimensional space where the waypoint of each particle is D , position is $\wp_n$, and velocity vector is V_n for n^{th} particle as follows:

$$\begin{aligned} \wp_n &= [\wp_{(n,1)}, \dots, \wp_{(n,D)}]^T \\ &= [(\wp^x, \wp^y, \wp^z)_{(n,1)}, \dots, (\wp^x, \wp^y, \wp^z)_{(n,D)}]^T, \\ V_n &= [V_{(n,1)}, \dots, V_{(n,D)}]^T \\ &= [(V^x, V^y, V^z)_{(n,1)}, \dots, (V^x, V^y, V^z)_{(n,D)}]^T, \end{aligned} \quad (20)$$

where the q^{th} waypoint position and velocity of n^{th} particle in space are represented as $q \in 1, \dots, D$; $(\wp^x, \wp^y, \wp^z)_{(n,q)}$, $(V^x, V^y, V^z)_{(n,q)}$. The swarm is given as if total particles in it are P .

$$[(\wp_1, V_1), \dots, (\wp_P, V_P)]. \quad (21)$$

In this algorithm having particles P , there is one global position and another individual best position e which are given as

$$\begin{cases} \wp_{(n,e)} = [\wp_{(n,1,e)}, \dots, \wp_{(n,D,e)}]^T = [(\wp^x, \wp^y, \wp^z)_{(n,1,e)}, \dots, (\wp^x, \wp^y, \wp^z)_{(n,D,e)}]^T, \\ \wp_e^G = [\wp_{(1,e)}, \dots, \wp_{(D,e)}]^T = [(\wp^x, \wp^y, \wp^z)_{(1,e)}, \dots, (\wp^x, \wp^y, \wp^z)_{(D,e)}]^T, \end{cases} \quad (22)$$

where $n \in 1, \dots, P$ is the number of particles. Furthermore, for multi-swarm function:

$$\begin{aligned} \wp_{(n,e)}(t+1) &= \begin{cases} \wp_{(n,e)}(t); \text{ if } f(\wp_{(n,e)}(t)) \leq F(\wp_n(t+1)), \\ \wp_n(t+1); \text{ if } f(\wp_{(n,e)}(t)) > F(\wp_n(t+1)), \end{cases} \\ \wp_e^G &\in (\wp_{(n,1,e)}, \dots, \wp_{(n,D,e)}), \\ F(\wp_e^G(t)) &= \min[F(\wp_{(e,1)}(t)), \dots, F(\wp_{(e,D)}(t))]. \end{aligned} \quad (23)$$

In a swarm, individual particle updates according to the following equation:

$$\begin{cases} \wp_{(n,q)}(t+1) = \wp_{(n,q)}(t) + V_{(n,q)}(t+1), \\ V_{(n,q)}(t+1) = \sigma \cdot V_{(n,q)}(t) + A_1 B_1 \cdot (\wp_{(n,q,e)}(t) - \wp_{(n,q)}(t)) + A_2 B_2 \cdot (\wp_{(G,q)}^e(t) - \wp_{(n,q)}(t)), \end{cases} \quad (24)$$

where the accelerating coefficients are A_1 and A_2 and B_1 and B_2 are two random variables which are 0 and 1. By modifying the inertia weight σ , it can be improved, and it stabilizes the global and local outcome through search procedure. Global search can be enhanced by increasing σ . To enhance local search, decrease σ , which is given as

$$\sigma = \frac{(\sigma_{\max} - \sigma_{\min})t}{W}, \quad (25)$$

where the current repetition is t , maximum repetition is W , and $\sigma_{\min}$ and $\sigma_{\max}$ signify the minimum and maximum values of σ .

6. Performance Evaluation

This section of the article weighs the enactment of the proposed CPSO with the help of simulations in MATLAB. The proposed algorithm is compared with PSO and evaluated. Table 1 presents the comparison of both algorithms in terms of the mean error for localization, cost, and efficiency. There is a total of 100 nodes having max and min errors. It clearly shows that the CPSO has attained an efficient output. The conclusion is that when nodes increase, the performance of CPSO also increases. The cost value for each particle is also presented which reveals the approach which still performs the best.

6.1. Mean Error for Localization (MEFL). The simulation output figure below shows the mean error for localization with several nodes. Figure 3 clearly shows that in PSO, the mean error for localization decreases as the number of nodes increases. But in CPSO, the situation is the opposite. The proposed algorithm shows very low localization errors. The advantage of having a large number of nodes is that it localizes the node with very low error.

6.2. Accuracy of CPSO. The accuracy in the percentage of the proposed algorithm CPSO is shown in Figure 4 along with the number of UAV nodes. It is clearly shown from the simulation output that when the number of nodes increases,

the CPSO attains a higher accuracy. Both the algorithms attain a higher accuracy due to a suitable number of adjacent nodes. Our proposed algorithm has an accuracy of about 98% when several nodes are at their maximum value.

6.3. Information Delivery Ratio (IDR). Figure 5 provides a comparison of IDR with the number of UAVs and shows the effectiveness of CPSO in delivering data of approximately more than 85%. The proposed algorithm shows the best performance as compared to PSO. At some points, the ratio of both algorithms is the same, but when the number of vehicles increases, the ratio of the proposed algorithm also increases, so they have a direct relationship with each other as shown.

6.4. Average End-to-End Delay. Figure 6 shows the evaluation of average end-to-end delay with the number of UAVs of both algorithms. The simulation output clearly shows that CPSO has significantly less average end-to-end delay as compared to PSO. In high mobility networks, the delay increases because time is mandatory to find the node position. Whenever the nodes move rapidly, there is more route breakage.

6.5. Cluster Making Period (CMP). CMP is defined as the time necessary to form a cluster by the algorithm. It takes time to make a cluster generally owing to the complexity of the algorithm. Whenever a CMP is greater, the energy consumption is very high as UAVs consume high energy. As shown in Figure 7, CPSO significantly takes less time to form a cluster as compared to PSO. It is clearly shown that when no nodes increase, the proposed algorithm works proficiently and takes less time which increases its efficiency. CPSO performs clustering much better than PSO. The search space of the proposed algorithm is reduced which affects the selection of node and CMP. As compared to many algorithms, CPSO takes a short period to obtain the solution needed. In conclusion, the energy and delay decrease with the decrease in CMP.

TABLE 1: Comparison of both algorithms in terms of localization error, cost, and efficiency.

Method	Total number of nodes	Max error for localization	Min error for localization	Mean error for localization	Mean cost	Efficiency (%)
CPSO	100	1.25	0.60	0.925	14.87	98
PSO	100	1.58	0.88	2.02	20.87	95

FIGURE 3: MEFL vs number of nodes.

FIGURE 4: Accuracy in percentage vs number of UAV nodes.

FIGURE 5: IDR vs number of UAVs.

FIGURE 6: End-to-end delay vs number of UAVs.

FIGURE 7: CMP vs number of nodes.

7. Conclusion

Designing an algorithm is complicated due to the dynamic topology changes and high mobility of the UAV network. This study presents the CPSO algorithm for UAV network communication which includes the coordination and routing among them. This algorithm is applied to solve node localization of UAVs in space and to solve combinational issues. It also reduces the combinational time and improves the performance of the swarms. The proposed algorithm has a convergence ability, reduces the localization error and end-to-end delay, and improves the accuracy and information delivery ratio. The simulation results show the performance of the proposed algorithm along with PSO. As a result, it is seen that CPSO is suitable for better performance in communication. CPSO has a greater ability to solve all the issues. Lastly, the overall fitness of the algorithm is increased. In the future, different algorithms based on AI will be studied to achieve high-speed localization and will be applied to solve different issues.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Ali Abbass was responsible for manuscript writing, data curation, and software. Vishal Dattana supervised the study, theorized this research, reviewed and edited the manuscript, and validated the study. Muhammad Saqib was responsible for software, data curation, and analysis. Bhawani Shankar

Chowdhry revised and edited the manuscript and examined the study.

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