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Development of an effective relay communication technique for multi-UAV wireless network

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ABSTRACT This paper proposes a novel relay algorithm to optimize the communication throughput of unmanned aerial vehicle (UAV) mobile relay formations while considering the challenges posed by obstacle avoidance, channel complexity, high dynamics of UAVs, and real-time mission requirements. To tackle the non-convex nature of this problem, we develop the unscented Kalman filter and hybrid particle swarm optimization (UKF-HPSO) algorithm. Initially, real-time prediction of the source and destination of UAV positions is accomplished using the UKF. Subsequently, these predicted coordinates serve as inputs for achieving the optimal deployment of relay UAVs under the constraints imposed by HPSO. The superiority of the UKF-HPSO algorithm compared to baseline approaches is demonstrated through extensive simulations. System throughput is effectively optimized while maintaining real-time performance by our proposed algorithm, which addresses the unique challenges of UAV communication in dynamic environments.

INDEX TERMS Unmanned aerial vehicle (UAV), relay communication, real-time optimization.

I. INTRODUCTION

Recently, with the advancement of unmanned aerial vehicle (UAV) and the miniaturization of communication equipment, UAVs equipped with communication devices have received increasing attention due to their rapid deployment and flexible operation [1]–[3]. To adapt to the burstiness of traffic demand and the uneven distribution of traffic in time and space, using UAVs as communication relay nodes for on-demand deployment has gradually become a research hotspot for beyond fifth-generation (B5G) and sixth-generation (6G) wireless networks [4], [5].

A. UAV RELAY MECHANISM

The UAV relay mechanism refers to the process of establishing a relay link with UAV as the intermediate node and transmitting data between two distant nodes. Its main purpose is to achieve data transmission between UAV and ground terminal or UAV and UAV. From the perspective of the channel, it can be divided into two aspects: Air-to-Ground (A2G) and Air-to-Air (A2A).

Zhan et al. [6] proposed a communication system that uses UAVs as relays between ground terminals and network base stations. To quantify the link performance, they defined the Ergodic Normalized Transmission Rate (ENTR) of the link between the ground node and the relay. The results verified the feasibility and excellent performance of using UAVs as relays. This study has led the trend in research on UAV relay communication, especially in the A2G direction, over the past decade. Zhou et al. [7] introduced an A2G and A2A cooperative vehicular networking architecture, where multiple UAVs are utilized as relays to assist the ground vehicular sub-network, forming an aerial sub-network. This two-layer cooperative networking scheme can be applied in various scenarios such as disaster rescue and pollution area investigation. This study explored the A2A direction of UAV relaying early on, providing insights for extending its applications.

In [8], Zeng et al. used UAVs as mobile relays to study maximizing throughput in a mobile relay system, with practical mobility constraints. The results show significant throughput gains by optimizing the relay's trajectory and power allocation, a method referenced in many later studies. For example, Zhang et al. [9] developed a solution for joint optimization of trajectory and power control, minimizing relay network interruption probability. The proposed scheme outperforms fixed power relays and circular trajectory schemes. Moreover, [10] optimized UAV trajectories and scheduling in post-disaster scenarios to provide wireless services for the ground equipment of surviving Base Stations (BSs), enabling information exchange between the disaster area and the outside world.

Researchers have considered more factors in the UAV relay mechanism, such as forwarding methods, channel models, and multiplexing techniques. In [11], reliability metrics were used to explore relay forwarding methods, showing that Decoding and Forwarding is more reliable than Amplify and Forward. [12] conducted a study on the channel model, considering Path Loss exponents and Small-Scale Fading, and constructed a practical wireless network analysis model. [13] studied a UAV-based mobile cloud computing system using Non-Orthogonal Multiple Access (NOMA) and Frequency Division Duplex (FDD), achieving lower energy consumption than local mobile execution methods.

Recently, the UAV relay mechanism has been combined with cutting-edge communication technologies, such as Mobile Edge Computing (MEC), Intelligent Reflecting Surfaces (IRS), and Integrated Satellite-Unmanned Aerial Vehicle-Terrestrial Networks (IS-UAV-TNs). In [14], UAVs and MEC servers provided services to multiple IoT terminals, optimizing bit allocation, time slot scheduling, and power allocation to minimize total energy consumption. [15] proposed a framework for an integrated relay system with UAVs and IRS, improving communication between ground nodes and optimizing system parameters. In [16], NOMA technology was combined with Cognitive Radio technology in the IS-UAV-TN framework to improve spectrum utilization. The paper also derived expressions for primary and secondary network traversal capacities, validating the mathematical derivation through simulation results and analyzing the impact of system parameters on transmission performance.

Overall, [6], [7] laid the foundation for relay research in both A2G and A2A directions, while [8]–[11], [13] enriched the relay mechanism in terms of throughput, forwarding methods, and multiplexing technologies. However, they employed relatively simplified approaches to channel modeling in communication scenarios, typically considering only line-of-sight (LOS) links. [12] introduced a path loss index correlated with height and considered small-scale fading, but did not construct a separate channel model for application scenarios. [14]–[16] combined UAV relay communication with cutting-edge technologies, taking channel conditions only as the foundation and focusing more on optimization at the application layer.

There is limited research on channel models in this field, particularly for high-rise dense urban scenarios. The channel parameters are not closely aligned with the real environment. Most studies adopt simplified channel models, with relatively few analyses of scenarios that simultaneously consider both LOS and non-line-of-sight (NLOS) links.

B. UAV PATH PLANNING

The main purpose of UAV path planning is to determine the most efficient and effective path for the UAV to reach its designated destination while fulfilling the necessary relay services. In order to achieve this goal, the path planning algorithm must take into account various factors such as the location and distribution of obstacles, the UAV's speed and altitude capabilities, the communication range of the relay network, and the overall mission objectives.

The mobile relay method proposed by Zeng et al. [8] has introduced research in the direction of path planning for UAV communication.

In the past decade, the development of path planning algorithms focused on two-dimensional (2D) environments has grown exponentially. However, due to physical, geometric, and time-related factors, these algorithms cannot help UAVs navigate in three-dimensional (3D) environments [17].

Starting with the path selection algorithm for UAVs, Wang et al. [18] studied the optimization of search path planning in multi-UAV relay scenarios. By optimizing the decision of choosing the information propagation path, the issues of interruption and distortion in UAV communication were improved. Wu et al. [19] designed an iterative algorithm based on the block coordinate descent method and Successive Convex Optimization (SCO) method, combined with UAV power control and path planning to optimize the communication scheduling of multiple users, and maximize the throughput of a multi-UAV assisted communication system. Zhao et al. [20] introduced Computational Intelligence (CI) methods into the UAV system and proposed an efficient path planning algorithm based on modeling and learning, which improves the performance of the communication network.

With the development of 5G communication in recent years, Al-Turjman [21] focused on network security issues, proposing a more comprehensive and detailed concept, including security behaviors such as network identification, authorization, deployment control, confidentiality, and availability.

In general, the mainstream UAV planning algorithms can be classified into different categories based on underlying principles and methods [22], as illustrated in Figure 1.

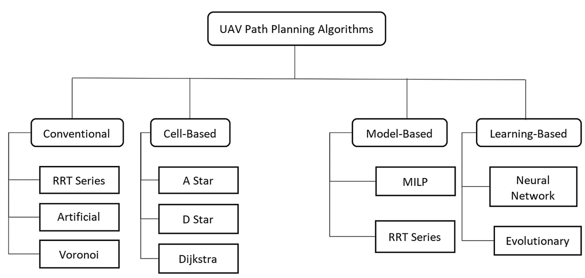

FIGURE 1. Mainstream UAV Path Planning Algorithms

Despite the introduction of various intelligent algorithms in [17], [19], current research in this field mostly involves non-real-time simulations of the entire flight trajectory of UAVs.

TABLE 1. Summary of Research on Optimization of UAV Communication

Reference	Optimization Aspect	Method	Key Outcome
Anazawa [23]	UAV Relay Trajectory	Genetic Algorithm	Maximization of data throughput in the access sequences of diverse user groups by optimizing UAV relay trajectory.
Kalantari [24]	UAV Relay Position	Particle Swarm Optimization	Optimal 3D positioning of UAV base stations for specific user communication rates; Minimized number of UAV stations.
Azari [25]	UAV Flight Altitude	Modeling Analysis	Optimal UAV altitude for maximum coverage; Relationship between coverage area and signal-to-noise ratio.
Mozaffari [26]	Multi-UAVs Deployment	Circle Packing Theory	Minimum number of UAVs for maximum coverage; Enhanced downlink range with lower power.
Lyu [27]	Multi-UAVs Deployment	Spiral Algorithm	UAVs approach target area from edge zone, overcoming strip-based algorithm limitations for minimum UAV coverage.
Arribas [28]	UAV 3D Deployment	Extreme Value Optimization	Proposed framework for 3D UAV network deployment and relocation for maximum coverage.
Ji and Wu [29]	UAV 3D Deployment	Gradient Descent	Improvement in UAV deployment performance compared to fixed relay and equal power allocation schemes.

These methods can meet overall functional requirements, and can be combined with other metrics for joint optimization [18], or incorporate cutting-edge thinking in the field [20]. However, planning the entire trajectory of UAVs directly from the source point to the endpoint without performing real-time calculations of UAV states at each point in time does not align with actual engineering application scenarios, indicating insufficient real-time performance.

C. UAV COMMUNICATION OPTIMIZATION

The optimization of UAV communication is a critical research area that aims to enhance the efficiency and reliability of communication in UAV networks by adjusting various parameters such as UAV position, speed, communication protocols, and routing algorithms. To evaluate the performance of UAV communication, researchers often use communication rate, throughput, interruption probability, and other indicators.

In the context of UAV relay communication, it is essential to deploy UAVs in three-dimensional space to ensure optimal resource allocation and meet the communication requirements of users. However, this approach presents numerous challenges, including power consumption, interference, and limited coverage range. Over the years, many studies have proposed innovative solutions to overcome these challenges, and Table 1 summarizes some of the key research in this field.

The genetic algorithm utilized in [23] may encounter local optima problems, where the population gets stuck and fails to escape because selection and crossover operations rely on the optimal solution of the current population. Similarly, the particle swarm optimization algorithm in [24] may also face the same issue, as some particles can get trapped in local optima and fail to escape due to the restricted updating mechanism. Although the spiral algorithm introduced in [27] is a relatively new optimization algorithm that can search for solutions in high-dimensional space, it is also susceptible to the problem of getting stuck in local optima. This issue of local optima is a common challenge faced by traditional optimization algorithms, especially when dealing with complex optimization problems.

In [25], [26], the simulation scenarios were simplified and did not consider practical constraints such as UAV flight speed. The scenario considered in [28] is more comprehensive, but the algorithm has strong limitations and is only suitable for solving specific problems. In [29], the 3D deployment of UAVs is related to the amplification factor, and a combination of Gradient Descent (GD) and convex optimization algorithm is used, but the presence of obstacles in the flight scenario is not taken into account. Currently, many algorithms are designed for a single scenario and lack scalability, with little consideration given to practical issues such as flight speed and obstacle avoidance.

In previous works, various optimization methods have been proposed to maximize throughput in multi-UAV communication systems [30]–[34]. For example, a block coordinate descent and successive convex optimization (SCO) algorithm was utilized in [35] to optimize communication scheduling, power control, and path planning. Cache-enabled UAVs were studied in [36], where enumeration search and caching optimization techniques were employed for optimal deployment. Another study [37] focused on throughput optimization in a non-orthogonal multiple access (NOMA)-based cognitive radio (CR) system with multi-UAV trunking, using a hybrid search method combining particle swarm optimization (PSO) and continuous genetic algorithm (CGA). However, these studies have overlooked important factors such as NLOS links and obstacle avoidance in complex flight scenarios. Additionally, they often assume static or slow-motion relays, which may not accurately reflect real-world UAV operations.

In addition, a number of reinforcement learning methods are currently being applied in this area [38]–[42]. In [43], a novel multi-agent deep reinforcement learning based algorithm called MAQMIX was developed for dual-hop UAV to minimize data transmission time and improve network throughput. In [44], the problem of maximizing the communication rate under guaranteed secure transmission constraints was considered, and the optimization of trajectory and transmit power was achieved using a proximal policy optimization (PPO)-based approach. However, these reinforcement learning methods rely on pre-training and also require high computational power in their derivation, which is not suitable for the easy deployment and high real-time performance required by algorithms for large-scale UAV application scenarios.

In this paper, we propose a novel approach that combines the unscented Kalman filter (UKF) algorithm with the hybrid particle swarm optimization (HPSO) algorithm to maximize the throughput in complex channels. The major innovations include

1) A more realistic simulation environment is constructed, i.e., relay nodes are considered to be moving at high speeds in three dimensions and the channel model contains NLOS and LOS factors.
2) A real-time high-precision 3D trajectory prediction algorithm is developed to fit the non-linear motion characteristics of UAVs.
3) Combining Simulated Annealing (SA), Adaptive Inertia Weights (AIW) and Penalty Function (PF), an HPSO-based optimisation algorithm is proposed to solve the non-convex problem of throughput optimization.

The remainder of this paper is organized as follows. Section II presents the channel model and the throughput model. Section III demonstrates the proposed optimization mechanisms, including an algorithm for real-time prediction of UAV 3D trajectories and an algorithm for optimizing UAV formation throughput. Section IV provides simulation results to validate that the proposed technique has better performance compared to baseline scheme. Finally, Section V concludes the paper.

II. SYSTEM MODEL

Fig. 1 shows a temporal discretization of the multi-UAV relay process, where the total duration is T, divided into N time points. Suppose that the source UAV (SUAV) and the destination UAV (DUAV) are required to perform different missions with uncorrelated trajectories and are therefore likely to leave their respective communication areas. Coupled with the presence of clutter channel fading and obstacles, it is necessary to deploy a relay UAV (RUAV) to help re-establish the communication link between the SUAV and the DUAV. In our model, mobile relaying is performed by decode and forward (DF) to ensure the reliability of data transmission, with each UAV having the same transmit power P_t and a sufficiently large buffer.

A. CHANNEL MODEL

To investigate the problem of relay communication in UAV formations, we establish an air-to-air channel model between

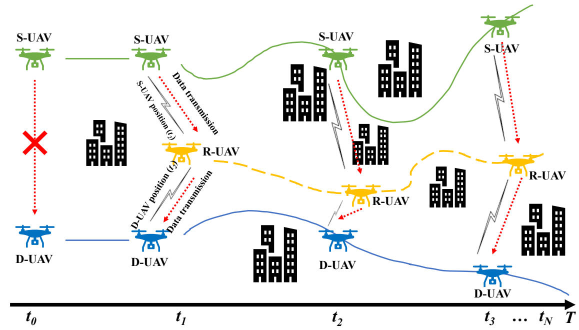

FIGURE 2. Illustration of the multi-UAV relay communication model.

UAVs. Considering the blockage of buildings, the channel transmission coefficient h is determined by the composite fading model composed of a Friis equation and a fading channel distribution with the height-dependent Rician factor.

Large-scale fading The large scale fading h_L takes the following form

$$h_L = \left(\frac{\lambda}{4\pi d}\right)^{\frac{\rho}{2}} 10^{\frac{\mathrm{RSS}-P_t-G_t-G_r}{10}} \tag{1}$$

where $RSS(dB)$ stands for received signal strength with the following form

$$RSS(dB) = P_t + G_t + G_r + 10\log_{10}\left(\frac{c}{4\pi d f_c}\right)^{\rho} \tag{2}$$

in which P_t is the transmit power, G_t is the transmit antenna gain of the UAV, G_r is the receive antenna gain of the UAV, f_c is the communication frequency, c is the approximation of the speed of light, d is the distance between the transmit and receive antennas in meters, and ρ is the path loss exponent, which is a constant corresponding to the flight environment.

Small-scale fading The probability density function of small-scale fading $f(x,h)$ can be written as

$$\begin{aligned} f(x,h) = {} & \frac{x}{\sigma^2(1+K(h))} \\ & \times \exp\left(-\frac{x^2+K(h)x^2}{2\sigma^2(1+K(h))}\right) I_0\left(\frac{x\sqrt{2K(h)}}{\sigma^2(1+K(h))}\right) \end{aligned} \tag{3}$$

$$h_S = \frac{\sqrt{\pi/2}\sigma(1+K(h))}{\sqrt{E[x]^2+Var[x]}} \tag{4}$$

where x is the amplitude of the signal, h_S represents the small-scale fading coefficient. $K(h)$ is the Rician factor dependent on UAV flight height, σ^2 is the power spectral density of the noise, and I_0 is the zero-order modified Bessel function to account for the effect of random phase on the signal amplitude, $E[x] = \sqrt{\frac{\pi}{2}}\sigma(1+K(h))$, $Var[x] = \frac{1}{2}(1-\frac{2}{\pi})\sigma^2(1+K(h))$.

We set the channel composite fading coefficient h as the product of h_L and h_S [45], which can be expressed as follows:

$$h = \left(\frac{\lambda}{4\pi d}\right)^{\frac{\rho}{2}} 10^{\frac{\mathrm{RSS}-P_t-G_t-G_r}{10}} \frac{\sqrt{\pi/2}\sigma(1+K(h))}{\sqrt{E[x]^2+Var[x]}} \tag{5}$$

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B. THROUGHPUT MODEL

Combining the channel conditions, the communication rates of the SUAV and RUAV are as follows:

$$C_{sr}[n] = B\log_2\left(1+\frac{h_{sr}[n]P_s}{P_n}\right) \tag{6}$$

$$C_{rd}[n] = B\log_2\left(1+\frac{h_{rd}[n]P_r}{P_n}\right) \tag{7}$$

where B represents the bandwidth of the channel, P_s and P_r denote the transmission power of the S-UAV and R-UAV, and P_n is the noise power at the receiving end. $h_{sr}[n]$ and $h_{rd}[n]$ represent the transmission coefficients based on (5).

At time n, the SUAV, DUAV, and RUAV are positioned respectively, at $X_{s[n]}(s_x[n], s_y[n], s_z[n])$, $X_{d[n]}(d_x[n], d_y[n], d_z[n])$ and $X_{r[n]}(r_x[n], r_y[n], r_z[n])$. The Euclidean spatial distance between the SUAV and RUAV is denoted as $d_{sr}[n]$, while the distance between the RUAV and DUAV is denoted as $d_{rd}[n]$. To ensure communication stability, obstacle avoidance, and adherence to UAV flight speed constraints, the formulated system throughput maximization problem is as follows:

$$\max \sum_{n=1}^{N} \frac{\min(C_{sr}[n], C_{rd}[n])S}{F\left(\frac{S}{C_{sr}[n]}+T_{\text{int}}+T_{\text{df}}\right)+F\left(\frac{S}{C_{rd}[n]}+T_{\text{int}}+T_{\text{df}}\right)} \tag{8a}$$

$$\text{s.t.}\quad C_{sr}[n] \geq C_{rd}[n] \tag{8b}$$

$$D_{\text{obs}}[n] \geq D_{\min}[n] \tag{8c}$$

$$|X_r[n+1]-X_r[n]| \leq V_{r\max} \tag{8d}$$

where F is the number of data packets transmitted, S is the size of each data packet, T_{int} is the fixed inter-transmission time, and T_{df} is the relay processing time. The distances from the obstacle and the minimum safe distance are denoted as $D_{\text{obs}}[n]$ and $D_{\min}[n]$ respectively. Additionally, $V_{r\max}$ represents the maximum flight speed of the RUAV.

III. PROPOSED OPTIMIZATION MECHANISM

A. REAL-TIME PREDICTION OF UAV 3D TRAJECTORIES

State Equation Based on the motion characteristics of the UAV, 9 parameters including coordinates, velocities, and accelerations in 3D are selected to construct the state equation:

$$X_k = AX_{k-1} + w_{k-1} \tag{9}$$

where X_k represents the state vector at time k, A is the state transition matrix and w_{k-1} is the process noise at time $k-1$.

Observation Equation Suppose the observation point is located at (x_0, y_0, z_0), the observation is based on the Euclidean distance in space, and the observation equation can be formulated as:

$$Z_k = \sqrt{(x-x_0)^2+(y-y_0)^2+(z-z_0)^2}+v_k \tag{10}$$

where Z_k and v_k represent the observation vector and the observation noise at time k, respectively.

Kalman filter assumes Gaussian distributions for states and observed variables, limiting its applicability to linear systems. To handle the non-linear characteristics of UAV flight, we incorporate the unscented transformation (UT) into the Kalman filter framework. The UT preserves the non-Gaussian distribution and enables efficient numerical computation, as demonstrated in Algorithm 1.

Algorithm 1 UKF-based UAV Trajectory Prediction

```
Input: Initial state X_0, initial covariance matrix P_0, process noise covariance matrix Q, measurement noise covariance matrix R, state transition function f, observation function h, number of sigma points n, scaling parameters α, β, κ
Output: Predicted UAV position p_{k+1}
for i = 0, ..., 2n do
    Calculate sigma-points X^i_{k-1} and weights W^i_m, W^i_c
end for
for i = 0, ..., 2n do
    Propagate sigma-points X^i_{k-1} through f to get X^i_{k|k-1}
end for
Compute predicted state X_{k|k-1} and covariance P_{k|k-1} using UT
for i = 0, ..., 2n do
    Transform propagated sigma-points X^i_{k|k-1} through h to get Z^i_{k|k-1}
end for
Compute predicted observation Z_{k|k-1} using UT
Compute Kalman gain K_k = P_{xz} S_k^{-1} using P_{xz} and S_k
Compute innovation y_k = Z_k - Z_{k|k-1}
Update state estimate X_k = X_{k|k-1} + K_k y_k
Update covariance matrix P_k = P_{k|k-1} - K_k S_k K_k^T
Apply state transition function f to predicted state X_{k|k-1}
return predicted UAV position p_{k+1}
```

B. UAV FORMATION THROUGHPUT OPTIMIZATION

Penalty Function (PF): The optimization problem formulated in (8a) has some constraints, so we introduce the PF in the fitness function of PSO to characterize these conditions as shown in (11).

$$\begin{aligned}\tilde{\max} \sum_{n=1}^{N} & \frac{C_{rd}[n]S}{F\left(\frac{S}{C_{sr}[n]}+\frac{S}{C_{rd}[n]}+2T_{\text{int}}+2T_{\text{df}}\right)} \\ & +\lambda_1 \min(0, C_{sr}[n]-C_{rd}[n]) \\ & +\lambda_2 \min(0, D_{\text{obs}}[n]-D_{\min}[n]) \\ & +\lambda_3 \min(0, V_{r\max}-|X_r[n+1]-X_r[n]|)\end{aligned} \tag{11}$$

where λ_1, λ_2 and λ_3 are penalty factors that control the effect of the constraints on the fitness function, which can penalize the particles that do not satisfy the constraints to prevent them from entering the infeasible region and gradually approaching the feasible region during the search.

Simulated Annealing (SA) Multi-UAV mobile relay optimization involves non-convex optimization under complex conditions. However, PSO is prone to local optima due to random initialization, limited global search and local information exchange, especially when solving such complex problems.

Algorithm 2 HPSO-based Throughput Optimization

Input: Coordinates of the SUAV $X_{s[n]}$ and DUAV $X_{d[n]}$, UAV flight parameters, terrain and obstacle parameters, penalty factors λ_1, λ_2 and λ_3
Output: Maximum system throughput, optimal deploy position of RUAV $X_{r[n]}$
Initialize: Initial temperature T_{SA}, cooling rate λ_{SA}, number of iterations *max_iter*, number of particles *pop_size*, personal best position *pbest*, global best position *gbest*, and channel transmission coefficients h
for $t = 1$ to M **do**
  for $i = 1$ to N **do**
    Update the particle position x_i^{t+1} and velocity v_i^{t+1}
    Evaluate the fitness function $f(x_i^{t+1})$
    Update the AIW ω_i^{t+1}
  end for
  for $i = 1$ to N **do**
    if x_i^{t+1} violates constraints **then**
      Apply the PF to x_i^{t+1}
    else
      if $f(x_i^{t+1}) \geq f(pbest_i^t)$ **then**
        $pbest_i^{t+1} = x_i^{t+1}$
      else
        if $T_{\text{SA}} > 1$ **then**
          if rand() $> e^{-|f(x_i^{t+1}) - f(pbest_i^t)|/T_{\text{SA}}}$ **then**
            $pbest_i^t = x_i^{t+1}$
          end if
          $T_{\text{SA}} = T_{\text{SA}} \cdot \lambda_{\text{SA}}$
        end if
      end if
    end if
    if $f(x_i^{t+1}) \geq f(gbest_i^t)$ **then**
      $gbest_i^{t+1} = x_i^{t+1}$
    else
      $gbest_i^{t+1} = gbest_i^t$
    end if
  end for
end for

To overcome this limitation, we propose incorporating the SA algorithm, a global optimization method based on random jumping, into the search strategy of the PSO algorithm. The SA algorithm simulates the crystallization process of metals, randomly exploring the solution space and accepting non-superior solutions with a certain probability [46]. This increases the chances of finding the global optimum and the probability can be expressed mathematically as:

$$p = \exp\left(-\frac{\Delta f}{T_{\text{SA}}}\right) \tag{12}$$

where p is the probability of accepting a sampled solution, T_{SA} is the current temperature, and Δf gives the difference in the fitness function for two generations of solutions. **Adaptive Inertia Weight (AIW)** The inertia weight is a crucial parameter in the PSO algorithm that balances global and local

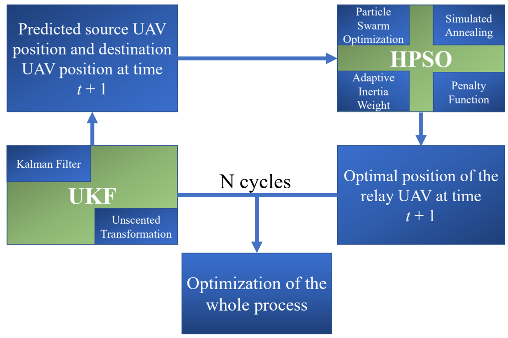


FIGURE 3. UKF-HPSO algorithm.

optimization during the search process [47]. Its classical form is expressed as:

$$\omega_t = \omega_{\max} - \frac{t(\omega_{\max} - \omega_{\min})}{t_{\max}} \tag{13}$$

where $\omega_{\max}$ and $\omega_{\min}$ represent the predetermined maximum and minimum values of the inertia weight, and $t_{\max}$ denotes the maximum number of iterations. In practical engineering scenarios, UAVs demand high maneuverability and real-time optimization performance. To address the unique solution situation of each particle, we introduce AIW as in Eq. (14), aiming to expedite algorithm convergence.

$$\omega_i^t = \begin{cases} \omega_{\min} + (\omega_{avg} - \omega_{\min}) \frac{(f_{\max}^t - f(x_i^t))}{(f_{\max}^t - f_{\text{avg}}^t)}, f(x_i^t) \geq f_{\text{avg}}^t \\ \omega_{\max} - (\omega_{\max} - \omega_{avg}) \frac{(f(x_i^t) - f_{\min}^t)}{(f_{\text{avg}}^t - f_{\min}^t)}, f(x_i^t) < f_{\text{avg}}^t \end{cases}$$

where $\omega_{\min}$ and $\omega_{\max}$ represent the predetermined minimum and maximum inertia coefficients, and $\omega_{avg} = \frac{\omega_{\min} + \omega_{\max}}{2}$. $f_{\text{avg}}^t, f_{\max}^t$, and $f_{\min}^t$ denote the average, maximum, and minimum fitness value of particles at the t-th iteration, respectively.

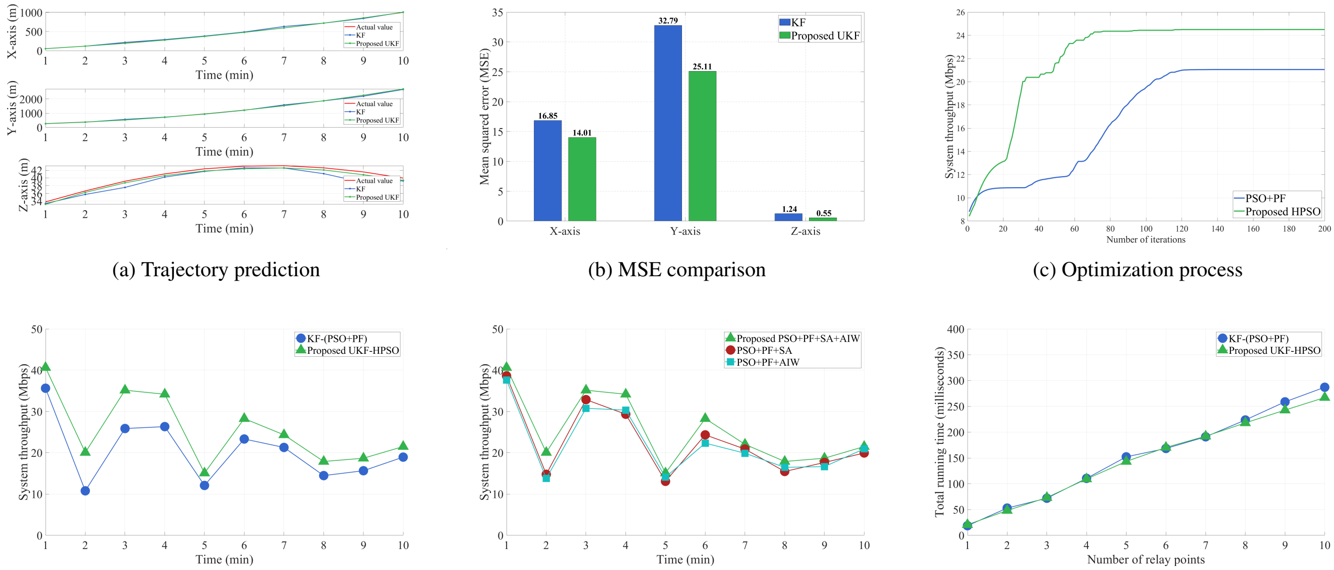
After incorporating PF, SA and AIW into PSO, the algorithm to optimize the throughput of multi-UAV mobile relaying is presented in Algorithm 2.

C. UKF-HPSO ALGORITHM

In a practical real-time engineering scenario, it is necessary to combine the proposed Algorithm 1 and Algorithm 2 to form an optimal multi-UAV mobile relay communication mechanism UKF-HPSO. The specific process is shown in Fig. 2. At each point in time, the R-UAV initially predicts the real-time trajectories of both the S-UAV and the D-UAV. Then it calculates the optimal relay deployment position, taking into account channel conditions and obstacle avoidance requirements. Ultimately, the R-UAV navigates to the position determined by the algorithm and re-establishes the communication link between the S-UAV and the D-UAV.

IV. NUMERICAL RESULTS

In this section, we present numerical results evaluating the performance of the proposed UKF-HPSO algorithm in comparison to other baseline schemes. The simulation parameters



(a) Trajectory prediction (b) MSE comparison (c) Optimization process

(d) Comparison experiment: throughput (e) Ablation experiment: throughput (f) Computational complexity

FIGURE 4. Simulation results of the proposed UKF-HPSO mechanism and the baseline mechanisms. (a)-(c) Split Comparison, (d)-(e) Overall assessment.

TABLE 2. Simulation Parameters

Parameter	Value	Parameter	Value
B	20 MHz	α	1×10^{-2}
f_c	2.4 GHz	β	2
P_s	27 dBm	κ	0
P_r	27 dBm	ρ	2.6
P_n	-90 dBm	m	1
G_t	5 dBi	n	9
G_r	5 dBi	max_iter	200
D_{min}	2 m	pop_size	30
T_{int}	10 ms	T_{SA}	500
T_{df}	50 ms	λ_{SA}	0.95
S	1 Mb	F	24

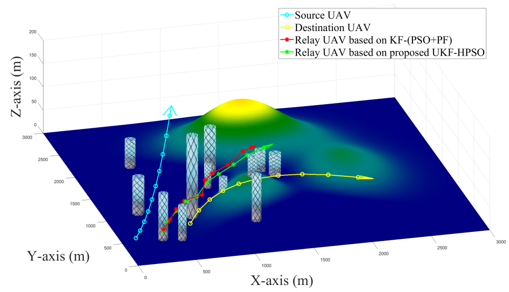


FIGURE 5. Demonstration of the complete flight trajectories optimized based on KF-(PSO+PF) / UKF-HPSO.

are outlined in Table 2 and the computational platform is a laptop equipped with an AMD Ryzen 9 5900HX CPU and 32 GB RAM. In addition, since the PSO algorithm does not contain constraints to execute (8b), (8c) and (8d) during the flight, we add PF to PSO as the baseline.

We first evaluate the performance of the proposed UKF algorithm and HPSO algorithm individually. Fig. 4(a) illustrates the superior real-time prediction results of the UKF algorithm for UAV 3D trajectories compared to the baseline KF. This difference is further quantified in Fig. 4(b) using the mean squared error (MSE). Additionally, Fig. 4(c) presents a comparison between HPSO and the baseline algorithm PSO+PF at the 7th time point. PSO converges to 21.04 Mbps after 127 iterations and becomes trapped in a local optimum. In contrast, HPSO achieves convergence to 24.34 Mbps by the 96th iteration, demonstrating significant improvement in convergence speed and overcoming the issue of premature convergence compared to PSO.

For the overall evaluation of the UKF-HPSO mechanism, Fig. 4(d) compares it with KF-(PSO+PF) for experiments. The simulation results show that UKF-HPSO achieves better optimisation results at each relay node, with an overall throughput improvement of about 28%. The contribution of SA and AIW is illustrated by the ablation of the individual components in the HPSO in Fig. 4(e). Fig. 4(f) shows the difference between UKF-HPSO and KF-(PSO+PF) in terms of running time for optimizing this problem. The solution of UKF-HPSO is faster in some of the complex nodes, i.e., nodes with low throughput due to building obstructions, but KF-(PSO+PF) is superior in the simpler optimization points. In general, the UKF-HPSO mechanism with the role of UT, SA and AIW achieves better results in the multi-UAV mobile relay throughput optimization problem without increasing the computational complexity compared to the baseline mechanisms. The flight trajectories of the multi-UAV mobile relay formation are shown in Fig. 5.

V. CONCLUSION

In this paper, we integrate concepts from automatic control into non-convex optimization and enhance the PSO algorithm, resulting in the development of the UKF-HPSO algorithm. Our results demonstrate the ability to overcome local optima and accelerate algorithm convergence without significantly increasing computational complexity, highlighting its superiority over the baseline approach. Compared to reinforcement learning methods used in this study, the UKF-HPSO algorithm offers advantages such as eliminating the need for pre-training, reducing computing power requirements, and enabling deployment on UAV platforms. This characteristic makes it highly suitable for large-scale UAV applications in complex and dynamic environments like post-disaster relief, military warfare, and resource exploration. By utilizing the UKF-HPSO algorithm, UAVs can autonomously navigate, make decisions, and ensure efficient and effective operations in challenging and dynamic circumstances.

REFERENCES

[1] M.-N. Nguyen, L. D. Nguyen, T. Q. Duong, and H. D. Tuan, "Real-time optimal resource allocation for embedded uav communication systems," *IEEE Wireless Communications Letters*, vol. 8, no. 1, pp. 225–228, 2019.

[2] F. Zhou, R. Q. Hu, Z. Li, and Y. Wang, "Mobile edge computing in unmanned aerial vehicle networks," *IEEE Wireless Communications*, vol. 27, no. 1, pp. 140–146, 2020.

[3] P. S. Bithas, V. Nikolaidis, A. G. Kanatas, and G. K. Karagiannidis, "Uav-to-ground communications: Channel modeling and uav selection," *IEEE Transactions on Communications*, vol. 68, no. 8, pp. 5135–5144, 2020.

[4] Z. Ullah, F. Al-Turjman, and L. Mostarda, "Cognition in UAV-aided 5g and beyond communications: A survey," *IEEE Transactions on Cognitive Communications and Networking*, vol. 6, no. 3, pp. 872–891, 2020.

[5] Z. Na, Y. Liu, J. Shi, C. Liu, and Z. Gao, "UAV-supported clustered noma for 6g-enabled internet of things: Trajectory planning and resource allocation," *IEEE Internet of Things Journal*, vol. 8, no. 20, pp. 15 041–15 048, 2021.

[6] P. Zhan, K. Yu, and A. L. Swindlehurst, "Wireless relay communications with unmanned aerial vehicles: Performance and optimization," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 47, no. 3, pp. 2068–2085, 2011.

[7] Y. Zhou, N. Cheng, N. Lu, and X. S. Shen, "Multi-uav-aided networks: Aerial-ground cooperative vehicular networking architecture," *ieee vehicular technology magazine*, vol. 10, no. 4, pp. 36–44, 2015.

[8] Y. Zeng, R. Zhang, and T. J. Lim, "Throughput maximization for uav-enabled mobile relaying systems," *IEEE Transactions on communications*, vol. 64, no. 12, pp. 4983–4996, 2016.

[9] S. Zhang, H. Zhang, Q. He, K. Bian, and L. Song, "Joint trajectory and power optimization for uav relay networks," *IEEE Communications Letters*, vol. 22, no. 1, pp. 161–164, 2017.

[10] N. Zhao, W. Lu, M. Sheng, Y. Chen, J. Tang, F. R. Yu, and K.-K. Wong, "Uav-assisted emergency networks in disasters," *IEEE Wireless Communications*, vol. 26, no. 1, pp. 45–51, 2019.

[11] Y. Chen, W. Feng, and G. Zheng, "Optimum placement of uav as relays," *IEEE Communications Letters*, vol. 22, no. 2, pp. 248–251, 2017.

[12] M. M. Azari, F. Rosas, K.-C. Chen, and S. Pollin, "Ultra reliable uav communication using altitude and cooperation diversity," *IEEE Transactions on Communications*, vol. 66, no. 1, pp. 330–344, 2017.

[13] S. Jeong, O. Simeone, and J. Kang, "Mobile edge computing via a uav-mounted cloudlet: Optimization of bit allocation and path planning," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 3, pp. 2049–2063, 2017.

[14] T. Zhang, Y. Xu, J. Loo, D. Yang, and L. Xiao, "Joint computation and communication design for uav-assisted mobile edge computing in iot," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 8, pp. 5505–5516, 2019.

[15] T. Shafique, H. Tabassum, and E. Hossain, "Optimization of wireless relaying with flexible uav-borne reflecting surfaces," *IEEE Transactions on Communications*, vol. 69, no. 1, pp. 309–325, 2020.

[16] K. GUO, R. LIU, C. DONG, K. AN, Y. HUANG, and S. ZHU, "Ergodic capacity of noma-based overlay cognitive integrated satellite-uav-terrestrial networks," *Chinese Journal of Electronics*, vol. 32, no. 2, pp. 1–10, 2023.

[17] F. Yang, X. Ji, C. Yang, J. Li, and B. Li, "Cooperative search of uav swarm based on improved ant colony algorithm in uncertain environment," in *2017 IEEE International Conference on Unmanned Systems (ICUS)*. IEEE, 2017, pp. 231–236.

[18] H. Wang, L. Peng, Z. Zhang, Z. Wang, X. Lei, and P. Zhao, "Path optimization of uav patrol and relay process," in *2018 2nd IEEE Conference on Energy Internet and Energy System Integration (EI2)*. IEEE, 2018, pp. 1–5.

[19] Q. Wu, Y. Zeng, and R. Zhang, "Joint trajectory and communication design for multi-uav enabled wireless networks," *IEEE Transactions on Wireless Communications*, vol. 17, no. 3, pp. 2109–2121, 2018.

[20] Y. Zhao, Z. Zheng, and Y. Liu, "Survey on computational-intelligence-based uav path planning," *Knowledge-Based Systems*, vol. 158, pp. 54–64, 2018.

[21] F. Al-Turjman, "Intelligence and security in big 5g-oriented iont: an overview," *Future Generation Computer Systems*, vol. 102, pp. 357–368, 2020.

[22] Z. Qadir, F. Ullah, H. S. Munawar, and F. Al-Turjman, "Addressing disasters in smart cities through uavs path planning and 5g communications: A systematic review," *Computer Communications*, vol. 168, pp. 114–135, 2021.

[23] K. Anazawa, P. Li, T. Miyazaki, and S. Guo, "Trajectory and data planning for mobile relay to enable efficient internet access after disasters," in *2015 IEEE Global Communications Conference (GLOBECOM)*. IEEE, 2015, pp. 1–6.

[24] E. Kalantari, H. Yanikomeroglu, and A. Yongacoglu, "On the number and 3d placement of drone base stations in wireless cellular networks," in *2016 IEEE 84th vehicular technology conference (VTC-Fall)*. IEEE, 2016, pp. 1–6.

[25] M. M. Azari, F. Rosas, K.-C. Chen, and S. Pollin, "Optimal uav positioning for terrestrial-aerial communication in presence of fading," in *2016 IEEE Global Communications Conference (GLOBECOM)*. IEEE, 2016, pp. 1–7.

[26] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Efficient deployment of multiple unmanned aerial vehicles for optimal wireless coverage," *IEEE Communications Letters*, vol. 20, no. 8, pp. 1647–1650, 2016.

[27] J. Lyu, Y. Zeng, R. Zhang, and T. J. Lim, "Placement optimization of uav-mounted mobile base stations," *IEEE Communications Letters*, vol. 21, no. 3, pp. 604–607, 2016.

[28] E. Arribas, V. Mancuso, and V. Cholvi, "Coverage optimization with a dynamic network of drone relays," *IEEE Transactions on Mobile Computing*, vol. 19, no. 10, pp. 2278–2298, 2019.

[29] A. Ji and J. Wu, "Joint deployment and power optimization for uav relay in multiuser networks," *Wireless Communications and Mobile Computing*, vol. 2022, 2022.

[30] T. Zhang, Y. Xu, J. Loo, D. Yang, and L. Xiao, "Joint computation and communication design for uav-assisted mobile edge computing in iot," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 8, pp. 5505–5516, 2020.

[31] L. Zhu, J. Zhang, Z. Xiao, X. Cao, X.-G. Xia, and R. Schober, "Millimeter-wave full-duplex uav relay: Joint positioning, beamforming, and power control," *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 9, pp. 2057–2073, 2020.

[32] J. Ji, K. Zhu, D. Niyato, and R. Wang, "Joint cache placement, flight trajectory, and transmission power optimization for multi-uav assisted wireless networks," *IEEE Transactions on Wireless Communications*, vol. 19, no. 8, pp. 5389–5403, 2020.

[33] S. Ahmed, M. Z. Chowdhury, and Y. M. Jang, "Energy-efficient uav relaying communications to serve ground nodes," *IEEE Communications Letters*, vol. 24, no. 4, pp. 849–852, 2020.

[34] F. Zeng, Z. Hu, Z. Xiao, H. Jiang, S. Zhou, W. Liu, and D. Liu, "Resource allocation and trajectory optimization for qoe provisioning in energy-efficient uav-enabled wireless networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 7, pp. 7634–7647, 2020.

[35] Q. Wu, Y. Zeng, and R. Zhang, "Joint trajectory and communication design for multi-UAV enabled wireless networks," *IEEE Transactions on Wireless Communications*, vol. 17, no. 3, pp. 2109–2121, 2018.

[36] B. Jiang, J. Yang, H. Xu, H. Song, and G. Zheng, "Multimedia data throughput maximization in internet-of-things system based on optimization of cache-enabled UAV," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 3525–3532, 2019.

[37] V.-H. Dang, L.-M.-D. Nguyen, V. N. Vo, H. Tran, T. D. Ho, C. So-In, and S. Sanguanpong, "Throughput optimization for noma energy harvesting cognitive radio with multi-UAV-assisted relaying under security constraints," *IEEE Transactions on Cognitive Communications and Networking*, vol. 9, no. 1, pp. 82–98, 2023.

[38] S. Khairy, P. Balaprakash, L. X. Cai, and Y. Cheng, "Constrained deep reinforcement learning for energy sustainable multi-uav based random access iot networks with noma," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 4, pp. 1101–1115, 2021.

[39] A. Koushik, F. Hu, and S. Kumar, "Deep Q -learning-based node positioning for throughput-optimal communications in dynamic uav swarm network," *IEEE Transactions on Cognitive Communications and Networking*, vol. 5, no. 3, pp. 554–566, 2019.

[40] O. S. Oubbati, M. Atiquzzaman, A. Baz, H. Alhakami, and J. Ben-Othman, "Dispatch of uavs for urban vehicular networks: A deep reinforcement learning approach," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 12, pp. 13 174–13 189, 2021.

[41] X. Lu, L. Xiao, C. Dai, and H. Dai, "Uav-aided cellular communications with deep reinforcement learning against jamming," *IEEE Wireless Communications*, vol. 27, no. 4, pp. 48–53, 2020.

[42] M. Samir, C. Assi, S. Sharafeddine, and A. Ghrayeb, "Online altitude control and scheduling policy for minimizing aoi in uav-assisted iot wireless networks," *IEEE Transactions on Mobile Computing*, vol. 21, no. 7, pp. 2493–2505, 2022.

[43] R. Ding, J. Chen, W. Wu, J. Liu, F. Gao, and X. Shen, "Packet routing in dynamic multi-hop uav relay network: A multi-agent learning approach," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 9, pp. 10 059–10 072, 2022.

[44] M. Shao, J. Yan, and X. Zhao, "Secrecy rate maximization by cooperative jamming for uav-enabled relay system with mobile nodes," *IEEE Internet of Things Journal*, pp. 1–1, 2023.

[45] W. Feng, J. Wang, Y. Chen, X. Wang, N. Ge, and J. Lu, "UAV-aided mimo communications for 5g internet of things," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 1731–1740, 2019.

[46] J. Bi, H. Yuan, S. Duanmu, M. Zhou, and A. Abusorrah, "Energy-optimized partial computation offloading in mobile-edge computing with genetic simulated-annealing-based particle swarm optimization," *IEEE Internet of Things Journal*, vol. 8, no. 5, pp. 3774–3785, 2021.

[47] J. Tang, G. Liu, and Q. Pan, "A review on representative swarm intelligence algorithms for solving optimization problems: Applications and trends," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 10, pp. 1627–1643, 2021.

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