ISSN: 0067-2904

Secure Flight Robotic Aircraft in Multi Constraints Landscape Using Parallel Hippo Swarm Optimization

Mohammed Hussein Ahmed [1]*, Ahmed Kareem Shibeeb [2], Mohamed Abdulrahman Abdulhamed [3], Rusul Hussein Hasan [4]

[1]Department of Computer Science, College of Education, Mustansiriyah University, Baghdad, Iraq
[2] Department of Computer Systems, Technical Institute - Suwaira, Middle Technical University, Baghdad, Iraq
[3] Department of Computer Science, Faculty of Computer Science and Information Technology, University of Basra, Basra, Iraq
4 University of Baghdad, Baghdad, Iraq

Received: 16/ 3/2025 Accepted: 26/ 8 /2025 Published: 30/ 8/2026

Abstract

Considering the rapid development of robotic aircraft (RA) in many applications, secure path planning in complex environments is a key field of study. This study converts path-planning into a multi-constraint optimization problem including terrain obstacles, radar emissions, path length, and fuel consumption. An improved Hippo swarm optimization (IHSO) is proposed to enhance the traditional HSO algorithm. The proposed IHSO enhances initial population diversity by using cubic chaos mapping and creates a parallel foraging environment to accelerate the algorithm's performance. The path planning information is encrypted using key policy attribute based encryption to provide a secure path planning model. The proposed algorithm was verified in urban and mountain environments and compared with four state-of-the-art algorithms: IPOA, MDBO, SLTSO, and HISOS-SCPSO. The IHSO successfully identified optimal paths with a mean of 84.916 and a standard deviation (SD) of 0.735 in an urban environment, consuming 0.716 s. Whereas, in the mountains, the consumption time was 14.984 s, with a mean of 109.314 s and an SD of 1.986. The experiments proved the superiority of the IHSO algorithm in terms of accuracy, running time, energy consumption, and stability.

Keywords: Robotic aircraft**,** Hippo swarm optimization, Key Policy Attribute Based Encryption (KPABE), Chaos mapping, Parallel computation.

تأمين طيران الطائرات الآلية في بيئة متعددة القيود باستخدام تحسين أسراب أفراس النهر المتوازية

محمد حسين احمد[1]* , احمد كريم شبيب[2], محمد عبدالرحمن عبدالحمي , رسل حسين حسن [4]

[1]قسم علوم الحاسوب, كلية التربية, الجامعة المستنصرية, بغداد, العراق
[2] قسم نظم الحاسوب, المعهد التقني – الصويرة, الجامعة التقنية الوسطى, بغداد, العراق
[3] قسم علوم الحاسوب, كلية علوم الحاسوب وتكنولوجيا المعلومات, جامعة البصرة, البصرة, العراق
[4] جامعة بغداد, بغداد, العراق

*Email: mohammedalbawi@uomustansiriyah.edu.iq

الخلاصة

بالنظر إلى التطور السريع للطائرات بدون طيار (RA) في مجالات متنوعه، برز تخطيط المسار الآمن للطائرات بدون طيار في البيئات المعقدة كمجال دراسي مهم. تُحوّل هذه الدراسة مشكلة تخطيط المسار إلى مشكلة تحسين متعددة القيود، بما في ذلك عوائق التضاريس، وانبعاثات الرادار، وطول المسار، واستهلاك الوقود. يُقترح خوارزمية مُحسّنة لسرب افراس النهر (IHSO) لتحسين خوارزمية HSO التقليدية. تُعزز IHSO المقترحة التنوع السكاني الأولي باستخدام رسم خرائط الفوضى المكعبة، وتُنشئ بيئة بحث موازية لتسريع أداء الخوارزمية. بالإضافة إلى ذلك، تُشفّر معلومات تخطيط المسار باستخدام تشفير قائم على سمات السياسة الرئيسية لتوفير نموذج تخطيط مسار آمن. تم التحقق من قدرة الخوارزمية المقترحة في البيئات الحضرية والجبلية، ومقارنتها بأربع خوارزميات متطورة: IPOA، وMDBO، وSLTSO، وHISOS–SCPSO. نجحت الخوارزمية المقترحة في تحديد المسارات المثلى بمتوسط 84.916 وانحراف معياري (SD) قدره 0.735 في بيئة حضرية معقدة، بمدة زمنية قدرها 0.716 ثانية فقط. بينما في بيئة جبلية معقدة، بلغ زمن الاستهلاك 14.984 ثانية، بمتوسط 109.314 ثانية وانحراف معياري قدره 1.986. أثبتت التجارب تفوق خوارزمية IHSO من حيث الدقة، وزمن التشغيل، واستهلاك الطاقة.

1. Introduction

Robotic aircraft (RA), also referred to as unmanned aerial vehicles (UAV) or drones, are powered flying machines or vehicles that may be operated remotely or automatically without an individual pilot and operator on board [1]. In civil fields such as agriculture, rescue operations, forest fire monitoring, and mapping, RAs are widely used for various purposes, including combat operations, military surveillance, and reconnaissance [2]. Ensuring the security of critical data requires encrypting sensitive information [3]. Owing to their usage in wireless networks, RA communication security cannot be guaranteed, making them vulnerable to attack. Considerable research has enhanced and preserved these functionalities for RA users [4].

In recent studies, providing optimal path planning for RAs in different environments has been considered as an optimization problem [5]. Planning a flight path over a large area is a common complex problem, where RAs need to find routes from starting points to destinations while avoiding obstacles, taking the shortest paths, keeping the calculations manageable, and ensuring they don't collide with anything [6]. Generally, when RAs operate in environments with multiple challenges, their path planning needs to consider factors like radar detection, air missiles, and energy use, which means the fitness function should focus on several goals at once [7].

Metaheuristic techniques are important methods for handling path planning problems for RAs in different scenarios [8]. The algorithms of the metaheuristic concept include four categories: swarm intelligence, evolutionary algorithms, hybrid algorithms, and physics-based algorithms [9]. Swarm intelligence (SI)-based metaheuristic algorithms are among the most significant global searches inspired by nature [10]. Hippo Swarm Optimization (HSO) imitates the behavior of hippopotamus groups in nature and is a new SI algorithm proposed in 2024. The population of the HSO algorithm is divided into the leader of the swarm, male leader, and female leader, where there are two considerations for each individual's position: positions in the water and land positions [11].

This paper suggests an improved HSO algorithm to provide secure routes for RAs in multi-constrained environments. The proposed algorithm enhanced the exploration searches of the traditional HSO while accelerating convergence toward optimal solutions. The key contributions of this research are summarized as follows:

1. A new application of an improved Hippo Swarm Optimization (HSO) algorithm for path planning in complex scenarios.
2. Integration of cubic chaos mapping and parallel foraging strategies to enhance convergence and computation speed.
3. Development of a multi-constraint mountain and urban environment model including terrain obstacles, radar emissions, path length, and fuel consumption.

The structure of this paper is as follows: examining the previous works in Section 2, Sections 3 and 4 illustrate the concept of traditional HSO algorithm and the details of an improved HSO algorithm respectively, consideration of the fitness function and encryption process of RA information are discussed in Section 5 and 6 respectively, in Section 7, the procedures of applying IHSO to find paths for RAs is presented, the performance of the proposed system is evaluated and analyzed in Section 8. Finally, Section 9 presents the conclusions of this study.

2. Related works

A lot of research has been done on how to plan routes for UAVs using different smart algorithms to help them fly safely. For example, R. Saeed and his team created a useful combined method to solve the path-planning issue for UAVs in a stable environment. This method mixes GA with Q-learning techniques to reduce the distance and energy use of UAVs while they complete specific tasks. The study found that this new combined method works about 57.14% better than the traditional GA when looking for the best path for RAs [12].
G. Ahmed and others simulated the CIPSO, PSO, IPSO, ABC, and GA techniques to find the optimal route for a drone in complex environments. This work focused on minimizing the energy consumption of drones without addressing the radar threats. The results from this study showed that the performance of the IPSO algorithm was better than that of other metaheuristic algorithms [13].

S. Qiu et al. suggested an improved Pelican Optimization Algorithm (IPOA) to solve path planning for UAVs in a multi-constrained environment. Compared to the traditional POA, the proposed algorithm enhances the path length by approximately 8.44%, distance to obstacles by approximately 4.07%, and flight time by approximately 9.36% [14]. L. Liu and others suggested an adaptive Sand Cat Swarm algorithm based on different strategies to specify the optimal route for UAVs. This work enhanced the convergence and diversity problems of the traditional Sand Cat Swarm, and a new algorithm was applied to determine the best path route for the UAV in a 3D environment with different threats. The multi-objective fitness is calculated to assess the performance of the candidate solutions, which are the smoothing, altitude, obstacles, and path length costs. The outcomes of this study demonstrated that the proposed technique could identify a shorter and smoother path from the starting point to the endpoint while maintaining relatively optimal consumption times [15].

Another important contribution was made by J. Zhang, X. Zhu, and J. Li, who suggested improvements to the traditional sparrow search algorithm to solve the path planning problem of UAVs in different environmental scenarios. The proposed algorithm is based on a cube chaotic map to enhance the initialization process and apply the firefly algorithm and tent chaos mapping search strategies to avoid low-speed convergence and local optimum problems. The results from this work proved the efficiency of the proposed algorithm compared the WOA, PSO, and SSA in terms of speed, length, and smooth flight routes; however, this work does not consider the terrain, energy constraints, and radar threats [16].

S. Liu and his colleagues presented an enhancement for the Crown Porcupine Optimizer (CPO) algorithm for RA route planning in a complex environment. The proposed algorithm improves the convergence and diversity problems of the traditional CPO algorithm. The improved CPO algorithm was applied to plan the route for UAVs in urban and mountainous terrains, and the results demonstrated the superiority of the improved CPO against traditional CPO and state-of-the-art research in terms of safety, length, and stability [17].

Q. Wang, M. Xu, and Z. Hu suggested a novel modification for the tuna swarm optimization algorithm (TSOA) to enhance the local and global search strategies. An improved algorithm updates the positions based on greedy and Lévy flight approaches to find the optimal path for UAVs in complex environments. The results from this study focused on the length and smoothness of the candidate path in a mountain environment without considering radar and other types of terrain threats. The improved TSOA was successful in allowing the UAV map to be stable and short routes from the start to the end points [18].

Y. Na et al. enhanced the PSO algorithm to allow UAVs to avoid mountainous terrain environments during flight. DDPG was used to adapt the parameters of the PSO algorithm to improve the search capability and avoid the local optimum problem. The experimental results of this work proved that an improved PSO algorithm was successful in reducing the fuel consumption of UAVs traveling in mountainous environments [19].

T. Xiong and his colleagues presented a hybrid method based on sine_cosine PSO and an improved symbiotic organism's search to find the optimal path planning for RA in urban and mountain environments. The results of this study indicated that the proposed hybrid technique can provide a smooth path for RA in a 3D environment with less time consumption [20]. Q. Shen and others enhanced the optimization ability of the dung beetle optimizer algorithm to find an efficient trajectory for drones. The new technique consumes considerable time to find the best route for a UAV in a static environment owing to the high complexity of the proposed algorithm [21].
Following this line of research, P. Saxena and R. Dewangan determined an optimal waypoint for UAVs by moving from source to goal points in a 3D environment with different obstacles based on the Salp Swarm Algorithm. The results from this research indicate that the new algorithm works better than other optimization methods like GSO, IBA, PSO, BBO, GWO, WOA, and SCA when it comes to being simple and quickly finding the best path in a static environment.

X. Sun et al. utilized combining intelligent water drop with the ACO algorithm to search for the best route planning for RA. The combined method improved the search for the best paths and tests, showing that these new techniques are better than the old ACO and IWD methods and some other advanced methods like MAACO, ACVDEPSO, IWD-DE, and CCO-AVOA.
S. Li and others proposed a hybrid technique to solve the path planning of UAVs in mountain environments. This work introduces a bio-inspired NN and improved Harris Hawks optimization algorithms to find multiple paths for UAVs in dynamic environments. Compared with the prior techniques, PSO, HHO, and SSA, the proposed BINN_HHO algorithm can avoid obstacles and find the best route for UAV [24].

X. Wang et al. introduced an optimization method to provide a safe UAV route in a multi-constraint environment. This work proposes a new modification to the Mayfly Algorithm (MA) to enhance exploration and exploitation capabilities. The modified MA is better than the traditional MA, GWO, PSO, and BOA at finding the best routes for UAVs in areas with many obstacles, but it does not take radar threats into account.
Despite significant progress, several researchers have explored UAV path planning using swarm intelligence algorithms. For example, Xiang et al. designed an improved ACO algorithm to solve the penetration problem of RAs in complex environments. The proposed technique allows the determination of the shortest path for RA under multiple threat factors, but this work does not account for the energy consumption of the RA when flying from the source to the destination [26].

C. Huang proposed an enhanced PSO algorithm to find an optimal path route of the fixed-wing RA in a 3D environment. This work used the divide and conquer technique with A* to improve the fast convergence and the global search problems of the traditional PSO algorithm. The performance of the proposed technique allows the RA to find the best flying path with multiple route points in a complex terrain environment; however, this work does not consider the radar and energy constraints [27].
B. Tong and his colleagues provided optimal path planning for UAVs using a multi-objective pigeon-inspired optimization algorithm. This work considers the smoothness, length, and risk of the UAV path from the source to the destination. The experimental results from this study illustrate the superiority of the proposed algorithm over other optimization methods [28]. W. Yu, J. Liu, and J. Zhou introduced an adaptive sparrow PSO algorithm to find the best route for UAVs in the building environment. The proposed algorithm applies variable speed for deadlock escapes and optimizes oscillation for trajectory smoothness to find the optimal real flight waypoints for UAVs in a building environment and does not explicitly consider radar threats and energy constraints [29].
In conclusion, the previous works have made significant strides in RAs' path planning using a range of intelligent optimization and hybrid algorithms, each focusing on specific aspects such as smoothing, path length, and avoidance of obstacles. However, many of these studies either neglect crucial constraints such as radar threats, energy consumption, and dynamic multi terrain conditions or have difficulties in simultaneously optimizing multiple conflicting objectives in a unified framework. Moreover, while several algorithms attempt to improve convergence speed and avoid falling into local optima, challenges remain in balancing exploitation and exploration effectively in multi constraint environment. To bridge these gabs, this work introduces a new application of an improved HSO algorithm, enriched cubic chaos mapping and parallel foraging strategies to accelerate convergence and robust performance. Additionally, this paper proposes a realistic multi constraint model and incorporates key policy attribute based encryption to ensure both optimal and secure path planning for Ras in urban and mountain scenarios.

3. HIPPO SWARM OPTIMIZATION (HSO)

The Hippo Swarm Optimization (HSO) is a new bio-inspired algorithm proposed by G. Zhou and others in 2024 to solve optimization and complex engineering problems [11]. The HSO algorithm imitates the natural behavior of hippopotamus groups, such as searching for food, movement, rivalry, and growth. The volume or mass of the hippo was not considered in the HSO algorithm, where each hippo was considered a point in the search problem and represented a solution for a specific optimization problem. Each hippo is assessed based on food resources, and the largest food resources are the best hippo swarm positions for survival.

The HSO algorithm divides the population into three categories: swarm leader, male leader, and female leader. Since hippos are amphibious animals, there are two considerations for this position. The first is for the best water positions, and the second is for the best land positions. There are current and historical global positions for both water and land. Figure 1 illustrates the flowchart of the traditional HSO algorithm.

4. An improved HSO algorithm (IHSO)

The HSO algorithm is a modern algorithm for solving optimization problems. To make the HSO algorithm work faster when finding the best path for UAVs in a complicated setting, it's recommended to use the chaos initialization method instead of the usual random start. Furthermore, the speed of the HSO algorithm in obtaining the best solutions is increased by providing a parallel computing environment for the evolution processes of hippos in the population.

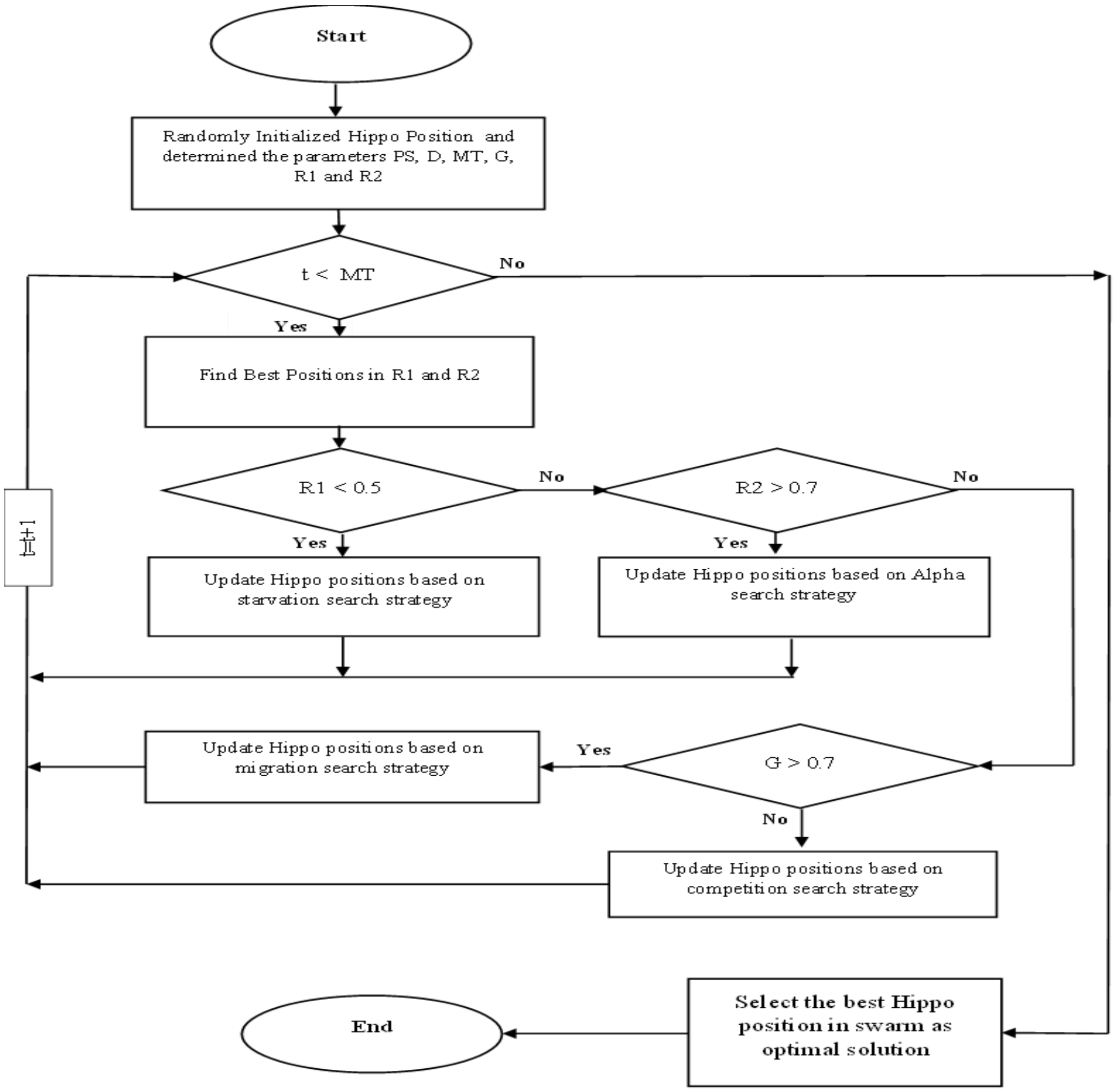

Figure 1: Flowchart of standard HSO algorithm.

4.1 Chaos mapping initialization

The initialization process is a critical step in optimization algorithms. The standard HSO algorithm initializes its population in a random manner, which may decrease the adaptability of individuals to find optimal solutions. This study enriches the diversity of the HSO population and reduces the probability of a lack of a local optimum by using cubic chaos mapping to produce chaotic variables for initializing the HSO population, as shown in Eq. (1). Figure 2 shows the statistical distribution of the population based on cubic chaos mapping [30].

$$a_{i+1} = 4^* a_i^3 - 3^* a_i \tag{1}$$

Where $-1 < a_i < 1$, i=0 to the size of population (SP). In the context of this study, each individual (hippo) in the population represents a candidate path for RA. The path is encoded as a vector of decision variables, where each dimension corresponds to a waypoint in 3D space (x,y,z). The full solution structure is a sequence of such waypoints that define the entire RA path from start to end points, while avoiding obstacles and threats.
Let (x, y, z) be the dimensionality of the problem; each hippo is encoded as:

$$\text{Hippo}_i = [x_1, y_1, z_1, x_2, y_2, z_2, \dots, x_n, y_n, z_n]$$

Where n is the number of waypoints, and i is the index of the individual in the population. This encoding captures the RA's path in 3D search problem, with each segment being a movement between two waypoints. The proposed initialization processes of the IHSO algorithm are:

1- Randomly determined SP Hippos in search space with upper and lower bounds (1, -1).
2- Each individual in the population is iterated according to Eq. (1).
3- Map the new positions of the individuals into a dimension of the solution space.

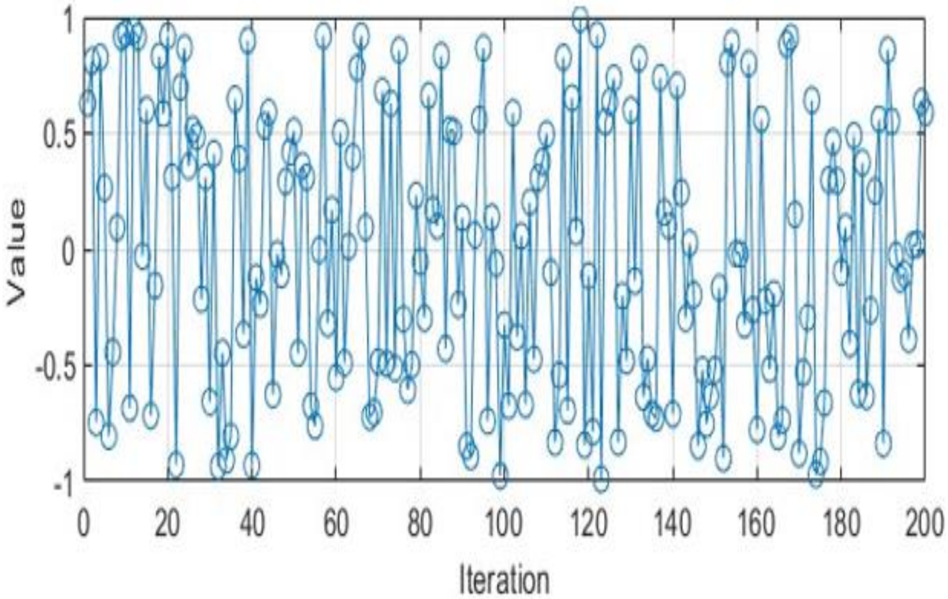

Figure 2: Initialization based on cubic chaos mapping**.**

The chaotic values are mapped to the solution space as seen in Figure 2, which can be observed over 100 generations, the population initialization exhibits strong variability across the full value range [-1, 1], and maintain significant fluctuation throughout the entire range of generations. This ensures that the initialization population is not clustered in any particular region, thus offering high exploration power at the start of the optimization process. As a result, the IHSO is better positioned to escape local optima and converge toward globally optimal solutions.

4.2 Foraging Behavior of IHSO

The foraging behavior of natural hippos was used as a model for the HSO. The population of the HSO was divided randomly into male, female, and baby hippos. All individuals in the population cooperate to determine the best food source. The process of searching for resources is divided into four strategies: starvation, alpha, migration, and competition searches. In the HSO algorithm, the behavior of the hippo depends on land and water food resources. Therefore, threshold values are used to control the evolution of individuals in a population [11]. Land (R1) and water (R2) food resources were calculated using the following equations:

$$R1= e^{-\frac{t}{t+T}} \tag{2}$$

$$R2= e^{\frac{t-T}{t}t} \tag{3}$$

Where T and t refer to the maximum and current iterations, respectively.

4.2.1 Starvation search

In the early iterations, individuals within the population were required to search a wide area for food resources in order to explore the search space. Therefore, the starvation search strategy begins when land food resources (R1) are less than the threshold value (TH1). Male and female hippos in the population follow partnerships with their group. To guide different search types for hippos, the hunger rates for male, female, and baby hippos were calculated based on Eqs. [4-7].

$$SR_a = e^{-\frac{O_a(r_a)}{Oa(i)}} \tag{4}$$

$$SR_b = e^{-\frac{O_b(r_b)}{Ob(i)}} \tag{5}$$

$$SR_{ca} = e^{-\frac{O_a(r_a)}{Oc(i)}} \tag{6}$$

$$SR_{cb} = e^{-\frac{O_b(r_b)}{Oc(i)}} \tag{7}$$

Where r_a, r_b are a random selection from the male and female hippo populations respectively, and i is hippo from the i_th male or female -hippo fitness.

The *SR* increases as the partner fitness value is good, which focuses the search for more resources around the partner. the foraging behavior of the male and female hippos in starvation search are calculated based on the following equations:

$$P_{a,i}^{t+1} = P_{a,i}^{t}(r_a) \pm 0.05 \times SR_a \times (R \times (U-L) + L) \tag{8}$$

$$P_{b,i}^{t+1} = P_{b,i}^{t}(r_b) \pm 0.05 \times SR_b \times (R \times (U-L) + L) \tag{9}$$

Where $P_{a,i}^{t}$ and $P_{b,i}^{t}$ refers to the positions of the male and female, respectively. R is a random number in the range [-1,1], U and L are the upper and lower bounds of the values search scope.

The Babies are assigned randomly to fathers and mothers in the population. The position of the hippo is updated based on the following equations:

$$P_{ca,i}^{t+1} = P_{a,i}^{t}(r_a) \pm 0.05 \times SR_{ca} \times (R \times (U-L) + L) \tag{10}$$

$$P_{cb,i}^{t+1} = P_{b,i}^{t}(r_b) \pm 0.05 \times SR_{cb} \times (R \times (U-L) + L) \tag{11}$$

$$P_{c,i}^{t+1} = \frac{P_{ca,i}^{t+1} + P_{cb,i}^{t+1}}{2} \quad (12)$$

4.2.2 Alpha search

Alpha search is the next stage in HSO foraging. During this stage, we narrow down the search for the best resources by focusing on R2. There are two conditions to begin the alpha search: R1 > 0.5 and R2 > 0.7. Alpha search is based on four positions: the best positions of the alpha hippo on land (BR1) and in water (BR2), the best position of the alpha hippo male (BHa), and the best position of the alpha hippo female (BHb). BR1 is the historically best position, whereas BR2 is the best position in the current iteration.

The hippo males (Ha) update their positions based on Eq. (13) and Eq. (14), which search around R1 and R2, whereas the hippo females (Hb) update their positions based on Eq. (15) and Eq. (16), which search for BR2 and Bha. Lastly, the hippo's baby updates their positions using Eq. (17) and Eq. (18), which determines that baby hippos aren't able to search alone, and they search around male and female leadership. The male, female, and baby hippos produced two candidate positions and randomly selected one position for the next iteration. The main characteristic of this stage is that there are different leaders in each hippo group, which can lead to better positions around the leaders.

$$P_{a,i}^{t+1}(R2) = BR2 \pm 2 \times R2 \times R \times \left(BR2 - P_{a,i}^{t} \right) \quad (13)$$

$$P_{a,i}^{t+1}(R1) = BR1 \pm 2 \times R2 \times R \times \left(BR1 - P_{a,i}^{t} \right) \quad (14)$$

Where $P_{a,i}^{t+1}(R2)$ and $P_{a,i}^{t+1}(R1)$ are the new positions of males around the best water and land resources.

$$P_{b,i}^{t+1}(R2) = BR2 \pm 2 \times R2 \times R \times \left(BR2 - P_{b,i}^{t} \right) \quad (15)$$

$$P_{ba,i}^{t+1}(Ba) = BP_{a}^{t} \pm 2 \times R2 \times R \times \left(BP_{a}^{t} - P_{b,i}^{t} \right) \quad (16)$$

Where $P_{b,i}^{t+1}(R2)$ and $P_{ba,i}^{t+1}(B)$ are the new positions of females around the best R2 and best P_{a}^{t}. BP_{a}^{t} is the best position of males at the current iteration.

$$P_{cb,i}^{t+1}(Ba) = BP_{a}^{t} \pm 2 \times R2 \times R \times \left(BP_{a}^{t} - P_{c,i}^{t} \right) \quad (17)$$

$$P_{ca,i}^{t+1}(Bb) = BP_{b}^{t} \pm 2 \times R2 \times R \times \left(BP_{b}^{t} - P_{c,i}^{t} \right) \quad (18)$$

Where BP_{b}^{t} refers to the best position of females at the current iteration.

4.2.3 Migration search

The third stage of the Hippo search strategy begins when resources become scarce in water (R2) and more abundant on land (R1), then the Hippo search strategy enters its third stage. Migration from water to land occurs especially when R1 > 0.5 and R2 < 0.7. The hippo's male searches the alpha male area, and the hippo's female mate crosses over with the hippo's male, who has more resources to ensure that they reach the best positions. The hippo baby still can't find the best positions alone, so it will follow the alpha male and female hippos. At this stage, the rate of migration (TR) was calculated based on Eqs. (20, 22, 24, and 25), and the percentage of food resources (PF) was considered, which was calculated using the following equation:

$$PF = \frac{F^2}{1 + F^2} \quad (19)$$

Where F refers to the food resources. These considerations led to the sharing of information between Hippo groups, and individuals who obtained good positions were allowed to abandon the pursuit of leaders. The hippo population in the migration search strategy updates its position based on Eqs. (21, 23, and 28).

$$TR_a = e^{-\frac{Oa(i)}{BO(R2)}} \tag{20}$$

$$P_{a,i}^{t+1} = P_{a,i}^{t} \pm 2 \times TR_a \times PF \times R \times \left(BR2 - P_{a,i}^{t} \right) \tag{21}$$

$$TR_b = e^{-\frac{O_b(i)}{O(BP_a^t)}} \tag{22}$$

$$P_{b,i}^{t+1} = P_{b,i}^{t} \pm 2 \times TR_b \times PF \times R \times \left(BP_a^t - P_{b,i}^{t} \right) \tag{23}$$

$$TR_{ca} = e^{-\frac{Oc(i)}{BO\left(P_b^t\right)}} \tag{24}$$

$$TR_{cb} = e^{-\frac{Oc(i)}{BO(P_a^t)}} \tag{25}$$

$$P_{cb,i}^{t+1} = P_c^t \pm 2 \times TR_{cb} \times PF \times R \times \left(BP_b^t - P_{c,i}^{t} \right) \tag{26}$$

$$P_{ca,i}^{t+1} = BP_b^t \pm 2 \times TR_{ca} \times PF \times R \times \left(BP_a^t - P_{c,i}^{t} \right) \tag{27}$$

$$P_{c,i}^{t+1} = \frac{P_{ca,i}^{t+1} + P_{cb,i}^{t+1}}{2} \tag{28}$$

4.2.4 Competition search

This search strategy has the same conditions as those used in the previous search. Therefore, a random number (Rand) exists to determine an appropriate strategy. We use a competition search when Rand is less than 0.7, and a migration search otherwise. In this strategy, competition occurs between hippos in the same group, so the males and females have competed with the same sex only, but the baby hippo competed with their parents because they couldn't compete with each other. Such an approach can help the algorithm to solve the local search problem. The population of hippos was updated based on the following equations:

$$P_{a,i}^{t+1} = P_{a,i}^{t} \pm 2 \times SR_a \times PF \times R \times \left(P_a^t(r_a) - P_{a,i}^{t} \right) \tag{29}$$

$$P_{b,i}^{t+1} = P_{b,i}^{t} \pm 2 \times SR_b \times PF \times R \times \left(P_b^t(r_b) - P_{b,i}^{t} \right) \tag{30}$$

$$SR_{ca} = e^{-\frac{O_a(r_b)}{Oc(i)}} \tag{31}$$

$$SR_{cb} = e^{-\frac{O_b(r_a)}{Oc(i)}} \tag{32}$$

$$P_{cb,i}^{t+1} = P_{c,i}^{t} \pm 2 \times SR_{cb} \times PF \times R \times \left(P_a^t(r_a) - P_{c,i}^{t} \right) \tag{33}$$

$$P_{ca,i}^{t+1} = P_{c,i}^{t} \pm 2 \times SR_{ca} \times PF \times R \times \left(P_b^t(r_b) - P_{c,i}^{t} \right) \tag{34}$$

$$P_{c,i}^{t+1} = \frac{P_{cb,i}^{t+1} + P_{ca,i}^{t+1}}{2} \tag{35}$$

4.2.5 Parallel Foraging Behavior of IHSO

Parallel computing allows multiple processors to execute tasks simultaneously to solve a problem more quickly [31]. Parallel foraging implemented for the IHSO algorithm in the MATLAB toolbox enables the distribution of computational tasks through multiple cores. This architecture accelerates the IHSO algorithm, enabling it to converge more quickly on the optimal secure path for robotic aircraft in complex environments.

We divide the hippo population into three subpopulations: males, females, and babies. In all four search strategies of the IHSO algorithm, the new positions of the male, female, and baby subpopulations are calculated at the same time on different threads using parallel functions in MATLAB, which then create the new population for the next generation. To minimize the inter-thread communication overhead, the IHSO algorithm is modified to calculate the objective values within each thread. Figure 3 shows a flowchart of IHOSO in a parallel environment.

Figure 3: Flowchart of the parallel foraging implementation for IHSO.

5. Multi constrains environment

There are multiple major factors for penetrating missions of robotic aircraft (RA) in complex environments, including radar threats, energy consumption, terrain threats, and the length of the path from the source to the destination [32]. RA must avoid terrain and radar emissions and find the shortest path with less fuel consumption.

5.1 Terrain factors

Modeling the environment for RA path planning is an essential challenge. This task requires data acquisition from a landscape model. In this work, two different terrain factors were considered to establish an artificial environment, including building and mountain factors [33]. We implement the mountain terrain model using the following equation:

$$C(c2, c3) = \sum_{i=1}^{m} f_i \exp\left[-\left(\frac{c2 - c2_i}{c2_{hi}}\right)^2 - \left(\frac{c3 - c3_i}{c3_{hi}}\right)^2\right] \tag{36}$$

Where the $c2, c3$ and C represents the coordinates position in a 3D environment. The total peak number is represented by m and the parameter f is used to control the height. The $c2_{hi}$ and $c3_{hi}$ are the x-axis and y-axis for the slope of the i_th peaks.

The second terrain factor, which is the building city, can be calculated based on the following equation:

$$C_1(c2, c3) = \sin(c3 + r1) + r2 \cdot \sin(c2) + r3 \cdot \cos\left(r4 \cdot \sqrt{c2^2 + c3^2}\right) + r6 \cdot \cos(c3) + r7 \cdot \sin\left(r8 \cdot \sqrt{c2^2 + c3^2}\right) \tag{37}$$

Where $r1$ to $r8$ are random coefficients that regulate the oscillation of the foundational terrain. The fitness function of the terrain consideration can be calculated based on the following equation:

$$TF = C + C_1 \tag{38}$$

5.2 Radar emissions factors

RAs are exposed to radar threats during navigation from the start to the target points. Therefore, drones must constantly adjust their course to avoid detection. When the RA is within the detection area of the radar, it is not entirely certain that it will be detected, particularly when its echo is below the threshold [34]. Radar threats are defined as the range of the radar beam, position of the RA, and echo received by the radar [35]. Suppose there are m radars within the RA path-planning environment. The echoes of these radars can be formulated as follows:

$$E_r^i(t) = Z_i \frac{A_i(t)}{D_i^4(t)} \tag{39}$$

Where $E_r^i(t)$ represents the echo of the i_th radars at t time and the $A_i(t)$ represents the RCS (Radar Cross Section) of the RA at t time where the $D_i^4(t)$ determined the distance between the radar and RA. Z_i is calculated according to the parameters of the radar, such as transmit power, antenna gain wavelength, propagation factor, and loss factor based on the following formula:

$$Z_i = \frac{P_t Tr^2 \lambda^2 R^4}{(4\pi)^3 C_B W} \tag{40}$$

Where P_t and Tr represent the power and the antenna gain of the transmitter, respectively. The λ represents the radar wavelength, R and W are the factors of the receiving or transmitting propagation and electromagnetic wave, respectively. The C_B refers to the coefficient between the signal waveform and the filter.

The probability of detection RA based on the echo representation of radars can be calculated according to the following equation:

$$B_i(t) = \begin{cases} \frac{E_r^i(t)}{L_i}, E_r^i(t) \geqslant L_i \\ 0, E_r^i(t) < L_i \end{cases}. \tag{41}$$

Where $B_i(t)$ refers to the ability to detect RA and L_i determines the threshold of the detection. To consider the detection distance of the radars, an empirical model is used as below:

$$D_{\lim}^i(t) = 4.12\left[\sqrt{H_i} + \sqrt{H(t)}\right] \tag{42}$$

Where $D_{\lim}^i(t)$ refers to the limited distance of the radar beam, H_i and $H(t)$ are the heights of the radar and RA, respectively. The RA will not detect when the distance between the radar and the RA is greater than $D_{\lim}^{i}(t)$. The radar capability of detection based on echo and range distance can be calculated based on Eq. (43), where Eq. (44) calculates the radar threat factor of the PA path planning (RF_r).

$$B_i(t) = \begin{cases} \frac{E_r^i(t)}{L_i}, E_r^i(t) \geqslant L_i; D_{\lim}^i(t) \geqslant D_i(t) \\ 0, E_r^i(t) < L_i; D_{\lim}^i(t) < D_i \end{cases}. \tag{43}$$

$$\mathrm{RF}_r(t) = \max_{1\leqslant i\leqslant M}[B_i(t)] \tag{44}$$

5.3 The factor of consumption energy

A shorter RA path length from the source to the destination results in lower energy consumption [36]. In this study, it was assumed that the RA speed through flight missions from the source to the destination was approximately constant. The factor of energy consumption (*EF*) of the RA was calculated based on Eq. (45):

$$EF = ß \times \sum_{t=1}^{n} \sqrt{(x_t - x_{t-1})^2 + (y_t - y_{t-1})^2 + (z_t - z_{t-1})^2} \tag{45}$$

Where ß refers to the energy coefficient of the parameter, x_t, y_t and z_t represented the trajectory waypoints.

5.4 Fitness function

Fitness function for the RA path-planning constraint by the RA kinematics model. In this study, fitness function (MF) was used to evaluate the candidate path for the RA from the start to the end points. The MF is minimized in this work and can be calculated using the following equation:

$$MF = \omega_1 TF + \omega_2 RF + \omega_3 EF \tag{46}$$

Where ω_1, ω_2 and ω_3 are the corresponding weights of the terrain threats, radar threats, and energy-consuming factors. The sum of ω_1, ω_2 and ω_3 weights must be equal to 1.

6. Encryption of RA's information

Unauthorized or hostile third-party techniques or users could potentially access sensitive data stored in RA sensors, which includes path planning information [37]. In this section, the protection of path-planning coordinates from man-in-the-middle attacks is implemented using a user access control system and encryption of data. KPABE, which refers to key policy attribute-based encryption, is used to provide a secure path-planning model RA in a multi-constraint environment [38]. KPABE has four algorithms: key generation, setup, encryption, and decryption. The master key (J) and public key (P) are generated based on the following equations:

$$\mathrm{P} = \{\mathrm{MD5(\ CR)}), BG_p, \mathrm{N}, \mathrm{m} = N^{\theta_2}, n = k^{1\theta_2}, e(\mathrm{N},\mathrm{N})^{\sigma^\circ}\} \tag{47}$$

$$\mathrm{J} = \{\theta_2, \mathrm{N}^{\theta^2}\} \tag{48}$$

Where *CR* refers to the candidate path for the drone, *BG* is a bilinear group with generator *N* and prime order *p*, θ_1 and θ_2 are relatively large primes to MD5 (*CR*) and belong to BG_p. The ciphertext is produced based on Eq. (48), where the plaintext (*PT*) and attributes are input to the algorithm together.

$$\mathrm{ET} = \{\mathrm{ET}^1 = PT, e(\mathrm{N},\mathrm{N})^{\theta_1,\mathrm{x}}, T, ET^2 = m^r, \mathrm{ET_x} = k^{q(x,0)}, ET_x^1 = H(A(\mathrm{x}))^{q(x,0)} \tag{49}$$

Finally, the user executed the decryption algorithm based on *USK* to reveal the plaintext and decrypt the ciphertext when granted access or null when not granted access.

7. Optimize RA path planning based on IHSO

IHSO is an adaptive bio-inspired algorithm designed for RA path planning. The IHSO searches the problem space to find an optimal or nearly optimal route from the start to the target points for the RA in a complex environment. In this study, the suggested algorithm starts by creating a group of possible solutions using cubic chaos mapping, with each Hipo in the group representing a potential path in the current generation. The IHSO algorithm creates a parallel computation environment that supports the four aging strategies of the traditional HSO, enabling it to find the best trajectory for RA in both urban and mountain environments with multiple constraints. Algorithm (1) presents the main steps of the proposed IHSO algorithm to optimize the path planning for RA. For clarity and ease of reference, Table 1 provides a list of the main symbols used throughout this paper.

Algorithm. 1. Steps of IHSO

```
Input IHSO parameters: PS, MT, Lb, Ub, D, …etc
Output: the best Hippo position as best path planning for RA
Initialized IHSO population based on Eq. (1)
Randomly divided population into male, female and baby Hippos
Calculated Fitness value for each individual based on Eq. (46)
Record the best position as best path planning for RA
For t =1 to MT do
    Calculated R1, R2 based on Eqs. (2) and (3).
    If R1 <0.5 then  / ( Starvation search)
        Update male position using Eq. (8)              |
        Update female position using Eq. (9)            | Concurrently
        Update baby position using Eq. (12)             |
    Else If R2 >0.7 then  / ( Alpha search)
        Update male position using Eqs. (13,14)         |
        Update female position using Eqs. (15,16)       | Concurrently
        Update baby position using Eqs. (17,18)         |
    Else If G >0.7 then  / ( Migration search)
        Update male position using Eq. (21)             |
        Update female position using Eq. (23)           | Concurrently
        Update baby position using Eq. (28)             |
    Else   (Competition search)
        Update male position using Eq. (29)             |
        Update female position using Eq. (30)           | Concurrently
        Update baby position using Eq. (35)             |
    End If
    Calculated Fitness value based on Eq. (46)
    Compare the previous best positions with current best position and update the best path planning for RA
    t=t+1
End for
Output the best Hippo position as an optimal solution
```

Table 1: Symbols description.

SYMBOLS	DESCRIPTION
PS	Population size [50-200]
MT	Maximum Iterations [50-500]
D	Dimension
LB	lower bound of search space
UB	Upper bound of search space
R1	Land food resource
R2	Water food resource
T	Current iteration
C1	Six mountains and four radar threats
C2	Twelve mountains and eight radar threats
C3	Eight obstacles with five threats from radar
C4	Twelve obstacles with eight threats from radar
AVF	Average value of fitness
BF	Best fitness
SD	Standard deviation
BRT1	Best running time before encryption
BRT2	Best running time after encryption

8. Experimental results

To demonstrate the effectiveness of the proposed IHSO, four previous evolutionary algorithms were employed for comparison: MDBO [21], HISOS-SCPSO [20], SLTSO [18], and IPOA [14], in addition to the traditional HSO algorithm. These methods have a relationship with the proposed IHSO. Four cases were implemented in this section, including two cases for simple and complex mountain environments and two cases for simple and complex urban environments, as shown in Table 2. Case one (*C1*) contained six mountains and four radar threats, whereas *C2* included 12 mountains and eight radar threats. *C3* and *C4* refer to the urban environment that contains eight obstacles with five threats from radar and twelve obstacles with eight threats from radar. All tests were implemented using R2022b software based on an 11th-generation laptop with Core i7-12900H, CPU@3.20 GHz, and 32 GB of RAM.

A map of the urban and mountainous environments was created randomly, and the area of the map was (1000, 1000, and 1000). The source and goal coordinates for RA in mountainous regions were established as (70, 40, 50) and (800, 950, 50), respectively, while the starting and ending sites in the urban environment were designated as (62, 12, 85) and (810, 950, 166). Table 3 presents the best fitness (BF), average fitness value (AVF), standard deviation (SD), and best running time (BRT) for the IHSO, HSO, MDBO, HISOS-SCPSO, SLTSO, and IPOA algorithms utilized to determine optimal path routes for RAs from starting points to target points in both mountainous and urban terrains.

Table 2: Parameters of the mountains and urban environments with radar threats.

No.	Mountains			Radar				No.	Urban			Radar			
	X	Y	Z	X	Y	Z	R		X	Y	Z	X	Y	Z	R
1	250	250	300	250	250	200	100	1	450	250	150	100	400	200	100
2	520	790	250	700	700	200	80	2	400	700	200	750	750	250	120
3	600	480	350	400	700	200	80	3	600	500	250	600	500	180	90
4	800	800	400	600	300	200	90	4	800	200	300	300	700	220	110
5	400	450	200	800	200	200	100	5	150	800	180	800	400	240	100
6	100	400	250	200	600	200	60	6	500	900	220	100	600	180	80
7	300	800	180	890	500	200	80	7	700	700	260	850	200	210	90
8	490	610	220	210	890	200	90	8	300	400	170	500	200	190	100
9	450	200	150					9	200	200	150				
10	300	600	250					10	590	730	240				
11	800	600	280					11	150	650	210				
12	700	300	500					12	850	405	230				

Table 3: The mountains and urban environments with radar threats.

Tools	Metrics	C1	C2	C3	C4	Tools	Metrics	C1	C2	C3	C4
IHSO	**Best**	**79.197**	**83.473**	**102.919**	**105.631**	**HISOS-SCPSO**	**Best**	79.903	83.810	106.607	111.362
	Mean	**79.681**	**84.916**	**104.035**	**109.314**		**Mean**	80.886	85.025	107.709	117.118
	SD	**0.095**	**0.735**	**0.805**	**1.986**		**SD**	0.552	1.023	1.197	2.351
	BRT	**0.291**	**0.716**	**6.973**	**14.984**		**BRT**	0.968	1.897	12.635	22.657
SLTSO	**Best**	80.561	85.031	108.951	113.259	**IPOA**	**Best**	79.861	83.790	105.031	110.925
	Mean	81.125	86.569	110.025	118.966		**Mean**	80.326	84.961	100.935	116.209
	SD	0.703	1.201	1.309	2.510		**SD**	0.357	0.924	1.025	2.204
	RT	0.661	1.619	10.865	20.030		**BRT**	0.621	1.519	10.510	18.692
MDBO	**Best**	82.365	87.103	110.139	117.307	**HSO**	**Best**	82.239	86.966	109.313	116.352
	Mean	83.036	88.559	111.619	123.702		**Mean**	82.997	88.126	11.092	122.917
	SD	0.863	1.526	1.637	2.990		**SD**	0.852	1.509	1.615	2.819
	BRT	0.831	1.773	11.336	21.925		**BRT**	0.819	1.699	11.035	21.339

The table above shows how well the IHSO algorithm works for finding the best routes for robotic aircraft (RA) in different environments, like mountains and cities. The IHSO algorithm consistently performed better than the other five optimization algorithms, HISOS-SCPSO, SLTSO, IPOA, MDBO, and HSO, in several important areas, such as path length, avoiding obstacles and threats, time efficiency, path smoothness, and energy use. These metrics are essential for ensuring the practicality and reliability of RA operations, particularly in real-world applications, where efficiency and safety are paramount. Table 4 and Figure 4 illustrate the performance impact of incorporating ciphertext policy encryption into the IHSO algorithm.

Table 4: The IHSO running times before and after the information encryption process.

Case	BRT1	BRT2	Overhead
C1	0.265	0.291	0.026
C2	0.639	0.716	0.077
C3	6.117	6.973	0.856
C4	13.030	14.984	1.954

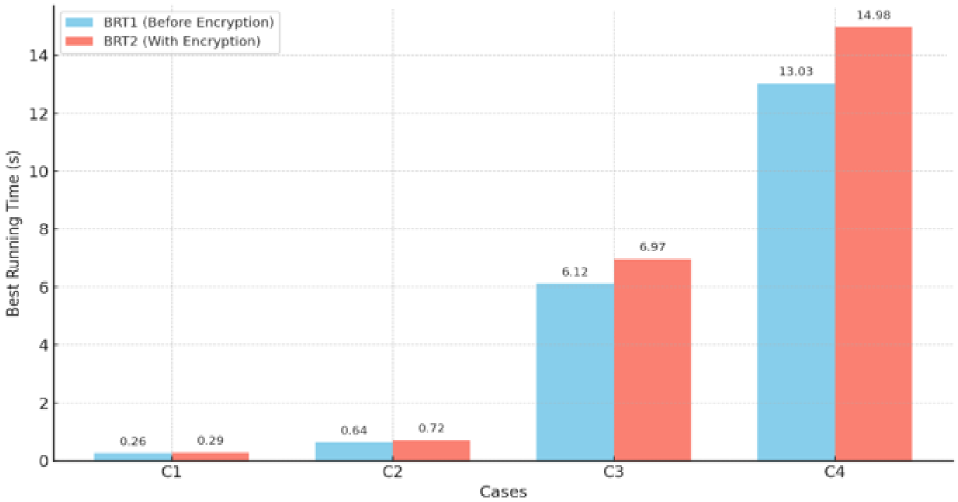

Figure 4: Comparison of IHSO Best Running Time (BRT) before and after applying ciphertext policy encryption.

The largest observed overhead was 1.95 s in C4, while the smallest was 0.026 s in C1. These values confirm that the integration of encryption does not significantly hinder optimization performance and support the practical viability of the proposed system.

Figure 5 shows the best fitness values and best running times of the IHSO and the other five optimization algorithms to find the best route from source to destination in mountain and urban flight scenarios, and Figure 6 illustrates the number of iterations required for each algorithm to obtain the best results.

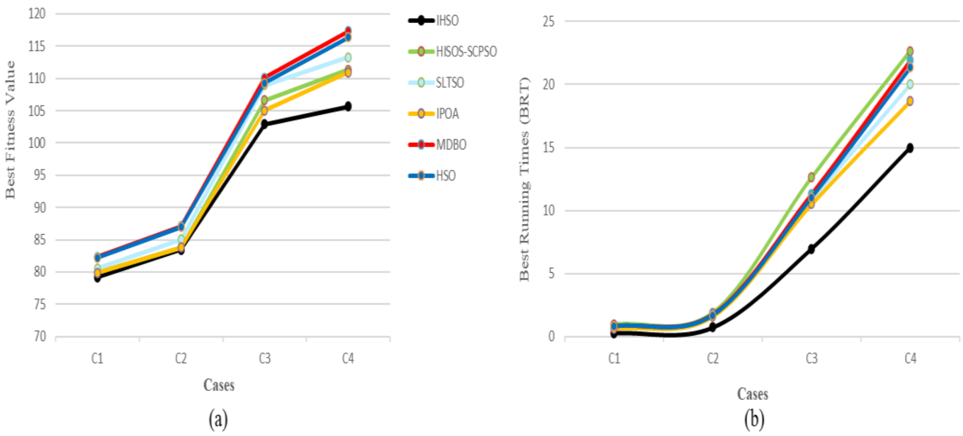

Figure 5: The performance of the IHSO in different environments: (a) The best fitness values of the proposed IHSO against related works, (b) the best consumption times of the proposed IHSO against related works.

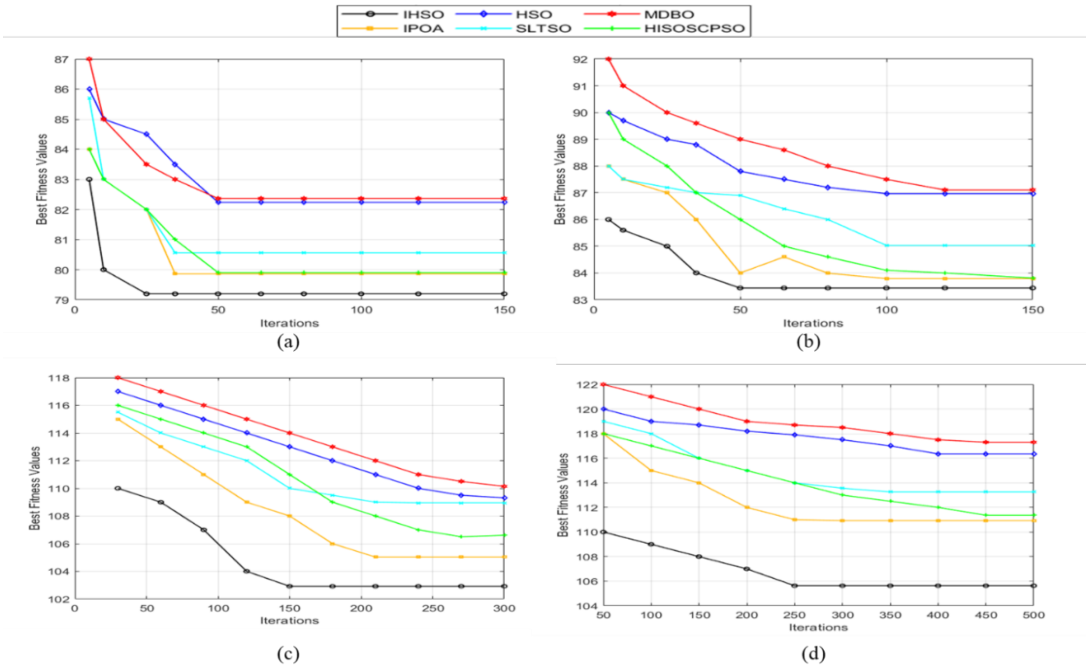

Figure 6: The number of iterations of the proposed IHSO algorithm against related works to find the optimal solutions: (a) In the C1 environment, (b) In the C2 environment, (c) In the C3 environment, (d) In the C4 environment.

Figure 5 provides a visual comparison of the best fitness values and running times for IHSO and the other algorithms, demonstrating that IHSO not only achieves the highest-quality solutions but also does so in significantly less time. For instance, in mountain flight scenarios (C1 and C2), the IHSO required only 0.291 and 0.735 s, respectively, to identify the optimal path. Even in more complex urban flight scenarios (C3 and C4), the IHSO maintained its efficiency, completing the task at 6.973 and 14.984 s, respectively. This remarkable speed is attributed to the parallel execution environment implemented in the proposed algorithm, which significantly enhances its computational efficiency. Figure 6 further supports these findings by showing the number of iterations required for each algorithm to converge to the best solution. IHSO consistently achieved convergence in fewer iterations, highlighting its robustness and ability to avoid local optima, which is a common challenge in path-planning optimization. Among the competing algorithms, IPOA demonstrated relatively good search performance, particularly in simpler scenarios, but it fell short of achieving the same level of precision and efficiency as IHSO. In contrast, MDBO delivered the worst fitness values across all scenarios, making it the least effective option for RA path planning. HISOS-SCPSO, while capable of generating viable waypoints for both mountain and urban environments, suffers from significantly higher computational times, which could limit its practicality in time-sensitive applications. The traditional HSO algorithm performed well in simple flight scenarios, exhibiting good speed and solution quality. However, in more complex environments, the HSO struggles with local optima, resulting in suboptimal paths. SLTSO has emerged as a promising alternative, demonstrating good results in identifying feasible paths. However, it cannot match the IHSO in terms of runtime efficiency or the quality of the objective function values, making it a less optimal choice for high-stakes applications.

Figure 7 visually summarizes the performance of all six algorithms by illustrating the best waypoints generated in the different scenarios. This figure underscores the superiority of IHSO in producing smoother, shorter, and more efficient paths than its counterparts. The IHSO's ability to consistently deliver high-quality solutions across varying levels of

environmental complexity solidifies its position as a leading algorithm for RA path planning. Its combination of speed, accuracy, and reliability makes it particularly well suited for real-world applications, where both performance and computational efficiency are critical.
In conclusion, the proposed IHSO algorithm is a highly effective solution for RA path planning and offers significant advantages over existing methods. Its ability to adapt to different environments, coupled with its computational efficiency, makes it a valuable tool for optimizing RA operations in both simple and complex scenarios. Future work could explore further enhancements of the algorithm, such as integrating additional constraints or adapting it to dynamic environments, to expand its applicability and robustness.

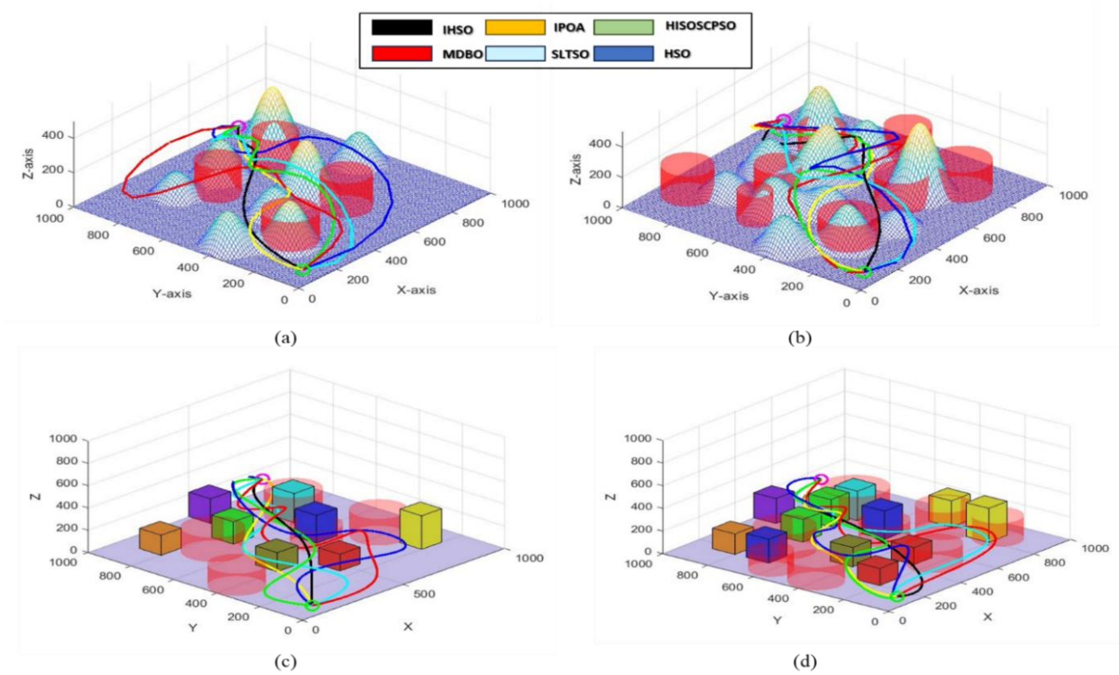

Figure 7: The best routes of the IHSO, HSO, MDBO, HISOS-SCPSO, SLTSO and IPOA from source to target points in different scenarios: (a) In the C1 environment, (b) In the C2 environment, (c) In the C3 environment, (d) In the C4 environment.

9. Conclusion

This paper examines the increasing demand for effective and reliable RA path planning in environments with multiple constraints. Two common environments were constructed: urban and mountainous terrain. A multi-objective fitness function is considered to incorporate objectives, such as avoiding terrain and radar emissions, finding the shortest path, and minimizing fuel consumption. An improved Hippo Swarm Optimization (IHSO) is proposed to enhance the global and local search strategies of the traditional HSO algorithm. The proposed IHSO algorithm initializes its population using cubic chaos mapping to avoid local optima by enriching the population diversity and providing a parallel computation environment for the four foraging strategies of the HSO algorithm, enabling efficient trajectory optimization for RAs in multi-constrained environments. Sensitive path planning information is protected using key policy attribute-based encryption to prevent man-in-the-middle attacks. The results demonstrate that the IHSO successfully identifies optimal and reliable routes for RAs across different environmental scenarios. In complex mountain environments, the IHSO achieved a fitness value of 83.473, with a standard deviation of 0.735, whereas in urban environments, it achieved a fitness value of 105.631, with a standard deviation of 1.986. Comparative analysis shows that the IHSO accelerates computation speeds by approximately 0.53, 0.60, 0.56, 0.63, and 0.38 times compared to IPOA, MDBO, SLTSO, HISOS-SCPSO, and HSO algorithms in mountain environments, and by 0.20, 0.32, 0.26, 0.34, and 0.30 times in urban environments, respectively. The proposed IHSO outperforms state-of-the-art algorithms in generating safe, short, smooth, and energy-efficient paths for RAs in multi-constrained 3D environments while maintaining optimal computation time.

10. Acknowledgements

This work was supported by the Mustansiriyah University, University of Basra, University of Baghdad, and Middle Technical University. Thank you for your help in successfully completing this research.

References

[1] M. Mahmood, N. Ghazal and F. Mahmood, "Optimizing Spatial Accuracy for Photogrammetric Processing of Drone-based 3D Mapping," *Iraqi Journal of Science*, vol. 65, no. 7, pp. 4124-4138, 2024.

[2] A. Qubaa, A. Hamdon and T. Al Jawwadi, "Morphology detection in archaeological ancient sites by using UAVs/drones data and GIS techniques," *Iraqi Journal of Science*, vol. 62, no. 11, pp. 4557-4570., 2021.

[3] M. H. Ahmed, A. K. Shibeeb and A. H. Mohammed, "Solve Polyalphabetic Cipher Based on Intelligent System," *2021 International Conference on Communication & Information Technology (ICICT)*, Basrah, Iraq, pp. 290-296, 2021.

[4] S. Ansari, L. Ahmad, S. Aziz Shah, A. Kashif Bashir, T. Boutaleb and S. Sinanovic, "Chaos-based privacy preserving vehicle safety protocol for 5G Connected Autonomous Vehicle networks,' *Transactions on Emerging Telecommunications Technologies*, vol. 31, no. 5, 2020.

[5] M. H. Ahmed, A. K. Shibeeb and M. B. Tuieb, "An Efficient Bio-inspired Technique for Secure Path Planning of Unmanned Aerial Vehicles in a 3D Environment," *International Journal of Intelligent Engineering & Systems*, vol. 17, no. 6, 2024.

[6] S. Aggarwal and N. Kumar, "Path planning techniques for unmanned aerial vehicles: A review, solutions, and challenges," *Computer communications*, vol. 149, pp. 270-299, 2020.

[7] J. Tang, H. Duan and S. Lao, "Swarm intelligence algorithms for multiple unmanned aerial vehicles collaboration: A comprehensive review," *Artificial Intelligence Review*, vol. 56, no. 5, pp. 4295-4327, 2023.

[8] C. Tan, R. Mohd-Mokhtar and R. Arshad, "A comprehensive review of coverage path planning in robotics using classical and heuristic algorithms," *IEEE Access*, vol. 9, pp. 119310-119342, 2021.

[9] G. Li, T. Zhang, C. Tsai, L. Yao, Y. Lu and J. Tang, "Review of the metaheuristic algorithms in applications: Visual analysis based on bibliometrics (1994–2023)," *Expert Systems with Applications*, no. 124857, 2024.

[10] Z. Ahmed, "Solving Adaptive Distributed Routing Algorithm Using Crow Search Algorithm," Iraqi Journal of Science, vol. 63, no. 12, pp. 5549-5558, 2022.

[11] G. Zhou, J. Du, J. Guo and G. Li, "A novel hippo swarm optimization: for solving high-dimensional problems and engineering design problems," *Journal of Computational Design and Engineering*, vol. 11, no.3, pp. 12-42., 2024.

[12] R. Saeed, E. Ali, M. Abdelhaq, R. Alsaqour, F. Ahmed and A. Saad, "Energy Efficient Path Planning Scheme for Unmanned Aerial Vehicle Using Hybrid Generic Algorithm-Based Q-Learning Optimization," in *IEEE Access*, vol. 12, pp. 13400-13417, 2024.

[13] G. Ahmed, T. Sheltami, M. Ghaleb, M. Hamdan, A. Mahmoud and A.Yasar, "Energy-Efficient Internet of Drones Path-Planning Study Using Meta-Heuristic Algorithms," *Applied Sciences*, vol. 14, no. 6, 2024.

[14] S. Qiu, J. Dai and D. Zhao, "Path Planning of an Unmanned Aerial Vehicle Based on a Multi-Strategy Improved Pelican Optimization Algorithm," *Biomimetics*, vol. 9, no. 10, 2024.

[15] L. Liu, Y. Lu, B. Yang, L. Yang, J. Zhao, Y. Chen and L. Li, "Research on a Multi-Strategy Improved Sand Cat Swarm Optimization Algorithm for Three-Dimensional UAV Trajectory Path Planning," *World Electric Vehicle Journal*, vol. 15, no. 6, 2024.

[16] J. Zhang, X. Zhu and J. Li, "Intelligent Path Planning with an Improved Sparrow Search Algorithm for Workshop UAV Inspection," *Sensors*, vol. 24, no. 4, 2024.

[17] S. Liu, Z. Jin, H. Lin and H. Lu, "An improve crested porcupine algorithm for UAV delivery path planning in challenging environments," *Scientific Reports*, vol. 14, no. 1, 2024.

[18] Q. Wang, M. Xu and Z. Hu, "Path Planning of Unmanned Aerial Vehicles Based on an Improved Bio-Inspired Tuna Swarm Optimization Algorithm," *Biomimetics*, vol. 9, no. 7, 2024.

[19] Y. Na, Y. Li, D. Chen, Y. Yao, T. Li, H. Liu and K. Wang, "Optimal Energy Consumption Path Planning for Unmanned Aerial Vehicles Based on Improved Particle Swarm Optimization," *Sustainability*, vol. 15, no. 16, 2023.

[20] T. Xiong, H. Li, K. Ding, H. Liu and Q. Li, "A Hybrid Improved Symbiotic Organisms Search and Sine–Cosine Particle Swarm Optimization Method for Drone 3D Path Planning," *Drones*, vol. 7, no. 10, 2023.

[21] Q. Shen, D. Zhang, M. Xie and Q. He, "Multi-strategy enhanced dung beetle optimizer and its application in three-dimensional UAV path planning. *Symmetry*, vol. 15, no. 7, 2023.

[22] R. Dewangan, P. Saxena, "Three-dimensional route planning for multiple unmanned aerial vehicles using Salp Swarm Algorithm," *Journal of Experimental & Theoretical Artificial Intelligence*, vol. 35, no. 7, pp. 1059-1078, 2023.

[23] X. Sun, S. Pan, N. Bao, and N. Liu, "Hybrid ant colony and intelligent water drop algorithm for route planning of unmanned aerial vehicles," *Computers and Electrical Engineering*, vol. 111, 2023.

[24] S. Li, R. Zhang, Y. Ding, X. Qin, Y. Han and H. Zhang, "Multi-UAV Path Planning Algorithm Based on BINN-HHO," *Sensors*, vol. 22, no. 24, 2024.

[25] X. Wang, J. Pan, Q. Yang, L. Kong, V. Snášel and S. Chu, "Modified mayfly algorithm for UAV path planning," Drones, vol. 6, no. 5, 2022.

[26] F. Xiang, K. Chen, J. Su, H. Liu and W. Zhang, "Penetration Planning and Design Method of Unmanned Aerial Vehicle Inspired by Biological Swarm Intelligence Algorithm," *Wireless Communications and Mobile Computing*, vol. 2021, no. 1, 2021.

[27] C. Huang, "A Novel Three-Dimensional Path Planning Method for Fixed-Wing UAV Using Improved Particle Swarm Optimization Algorithm. *International Journal of Aerospace Engineering*, vol. 2021, no. 1, 2021.

[28] B. Tong, L. Chen and H. Duan, "A path planning method for UAVs based on multi-objective pigeon-inspired optimization and differential evolution," *International Journal of Bio-Inspired Computation*, vol. 17, no. 2, pp. 105-112, 2021.

[29] W. Yu, J. Liu and J. Zhou, "A novel sparrow particle swarm algorithm (SPSA) for unmanned aerial vehicle path planning. *Scientific programming*, vol. 2021, no. 1, 2021.

[30] C. Wang, Y. Di, J. Tang, J. Shuai, Y. Zhang and Q. Lu, "The dynamic analysis of a novel reconfigurable cubic chaotic map and its application in finite field," *Symmetry*, vol. 13, no. 8, 2023.

[31] A. Nsaif and F. Abbood, "A parallel extended fuzzy c-mean algorithm for enhanced color image segmentation," In *AIP Conference Proceedings*, vol. 3036, no. 1, 2024.

[32] J. Saunders, S. Saeedi and W. Li, "Autonomous aerial delivery vehicles, a survey of techniques on how aerial package delivery is achieved," *Journal of Field Robotics*, PP. 1-47, 2023.

[33] L. Deng, H. Chen, X. Zhang and H. Liu, "Three-dimensional path planning of UAV based on improved particle swarm optimization," *Mathematics*, vol. 11, no. 9, 2023.

[34] X. Chai, Z. Zheng, J. Xiao, L. Yan, B. Qu, P. Wen and H. Sun, "Multi-strategy fusion differential evolution algorithm for UAV path planning in complex environment," *Aerospace Science and Technology*, vol. 121, 2022.

[35] J. Luo, Q. Liang and H. Li, "UAV penetration mission path planning based on improved holonic particle swarm optimization," *Journal of Systems Engineering and Electronics*, vol. 34, no. 1, pp. 197-213, 2022.

[36] B. Zhu, E. Bedeer, H. Nguyen, R. Barton and J. Henry, "UAV trajectory planning in wireless sensor networks for energy consumption minimization by deep reinforcement learning," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 9, pp. 9540-9554, 2021.

[37] H. Hadi, Y. Cao, K. Nisa, A. Jamil and Q. Ni, "A comprehensive survey on security, privacy issues and emerging defence technologies for UAVs," *Journal of Network and Computer Applications*, vol. 213, 2023.

[38] Y. Yu, J. Shi, H. Li, Y. Li, X. Du and M. Guizani, "Key-policy attribute-based encryption with keyword search in virtualized environments," *IEEE Journal on Selected Areas in Communications*, vol. 38, no. 6, pp. 1242-1251, 2020.