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Path Planning via Swarm Intelligence Algorithms in Unmanned Aerial Vehicle Population

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Abstract: Unmanned Aerial Vehicle (UAV) is an autonomous aerial vehicle capable of operating autonomously or in swarm cooperation, performing various tasks in civilian and military domains that exceed human capabilities. These vehicles, which can be produced in different models with varying hardware and software features, include flight control systems, route tracking systems, sensors, and numerous additional components. UAVs have the ability to process data from themselves, the control center, and the external environment. Data processing enables functions such as flight management, swarm optimization, and target and route analysis. In this analysis process, optimization algorithms and especially swarm intelligence algorithms inspired by creatures that move in flocks in nature are used. In this study, the aim was to determine the optimal route and distance from 10 different coordinate points for collective task optimization within a UAV swarm. Artificial Bee Colony (ABC) Optimization and Particle Swarm Optimization (PSO) were used during the task optimization process. The application was coded in Python. As a result of the application, the optimal distance was calculated as 0.123 km for the ABC algorithm and 0.167 km for the PSO algorithm. In addition, both algorithms determined the best routes according to different start and end points in route planning task optimisation.

Keywords: UAV, Path planning, Swarm intelligence algorithms, ABC optimization, PSO

Introduction

Many risky and challenging tasks are carried out by a team consisting of multiple members. The success of the task relies on the collaboration and coordination exhibited by team members. Task optimization is defined as the interaction of team members with the goal of maximizing or minimizing an objective function. Task optimization aims to improve decision-making processes that involve numerous variables and constraints. This method is utilized to optimize one or more objective functions simultaneously, enabling the concurrent optimization of various objectives under the interaction of numerous variables.

Task optimization is applied in industrial design, engineering, manufacturing processes, finance, logistics, energy management and similar fields. This method often uses evolutionary algorithms, genetic algorithms, natural language processing, artificial neural networks, or various mathematical optimization techniques. Task optimization is an important tool for optimizing decision-making processes, reducing costs and using resources more effectively. Mission optimization in flying systems is especially used to optimize flight time, flight speed, energy consumption and path planning. Path planning refers to the process by which an autonomous system finds the safest and most appropriate path from a given starting point to a given destination point. During this process, multi-dimensional planning is made such as efficient use of resources, adaptation to environmental conditions and calculation of alternative routes. As output at the end of the plan, it calculates the optimum distance and route suitable for the mission objective function.

Task optimization in a UAV team exhibiting swarm behavior is defined as a metaheuristic optimization technique inspired by nature and social organizations. This technique typically involves members of a group

- Selection and peer-review under responsibility of the Organizing Committee of the Conference called "particles" or "agents" collaborating throughout the task process. Each member explores the potential solution space and shares knowledge through interaction with other members and works together to develop potential solutions. Herd optimization is especially effective in solving complex problems in disciplines such as engineering, fleet management, logistics and finance.

Many of the autonomous capabilities that swarms exhibit in task optimisation processes have traces of artificial intelligence (AI). This swarm AI is defined as the ability of a group of similar organisms or objects to interact while exhibiting complex collective behavior to achieve common goals based on local knowledge. Research on swarm intelligence aims to understand and improve collective behaviors by examining the internal interactions of the system, leadership structures, information sharing and coordination. Additionally, swarm intelligence is widely used to optimize objective functions such as communication, location verification and path planning in swarms of vehicles that exhibit autonomous behavior, such as UAVs.

In this study, a general introduction will be given to mission optimization techniques and swarm intelligence algorithms applied to UAV swarms. Then, an optimization application will be carried out to determine the best route in a mission scenario using some swarm intelligence algorithms. In this scenario, firstly, the flight parameters of the UAV swarm, mission boundaries and transit coordinates on the map were determined. Then, ABC and PSO algorithms, which are swarm intelligence algorithms suitable for the task objective function, were prepared. Finally, the scenario was coded in the Python programming language.

The architecture of the article is as follows. In Chapter Two, the conceptual framework of UAV mission optimization, swarm intelligence, and optimization algorithms is presented along with the literature review. Section 3 describes the architecture, scenario, and methodology of an example path planning task optimization. Additionally, this section introduces the parameters used in the path planning process, swarm intelligence algorithms, and the algorithm of the program developed in Python. In the fourth section, the values calculated for task optimization within the scenario and the visual outputs of these values when the Python program is run are presented. In the conclusion section, a general evaluation of the application is made. It is believed that this study will make significant contributions to future research on path planning task optimization in UAV swarms.

Conceptual Framework

This section contains information about the UAV's swarm structure, swarm intelligence, task optimization and AI algorithms used in swarm intelligence optimization.

UAV Swarm Structure

UAV, also called a drone, is a semi or fully autonomous aerial vehicle that utilizes electronic communication and control subsystems (Puente Castro et al., 2022). UAVs are autonomous aerial robotic systems capable of independently performing takeoff, flight, mission execution, and landing activities, and, in some cases, making autonomous decisions (Cosar, 2022). Although UAVs have different features and limitations in terms of software and hardware, they can exhibit complementary features when they come together to form a swarm. Such features are seen in many living populations in nature.

The successful completion of a common mission over vast geographical areas by multiple UAVs depends on the collective behaviors of all members, which involve cooperation, coordination, and communication. UAV swarms establish communication with ground stations, their own members, and other systems using wireless network technologies. The quality of this communication is expected to be flawless, uninterrupted and protected against attacks. This is crucial because a communication failure can lead to UAV collisions, deviations from the swarm, and mission failure.

For a UAV swarm to self-organize, it relies on network formation and the effective integration of local computing functions. This system, which behaves as two separate components, has complementary features. For example, the network formation system within the swarm can calculate new routes in real-time to prevent the swarm from suffering in adverse situations such as packet loss or cyberattacks during communication (Gupta et al., 2015). Cosar and Kıran (2021) proposed a blockchain-based collaborative network model between UAV swarms to increase their location accuracy against cyber-attacks.

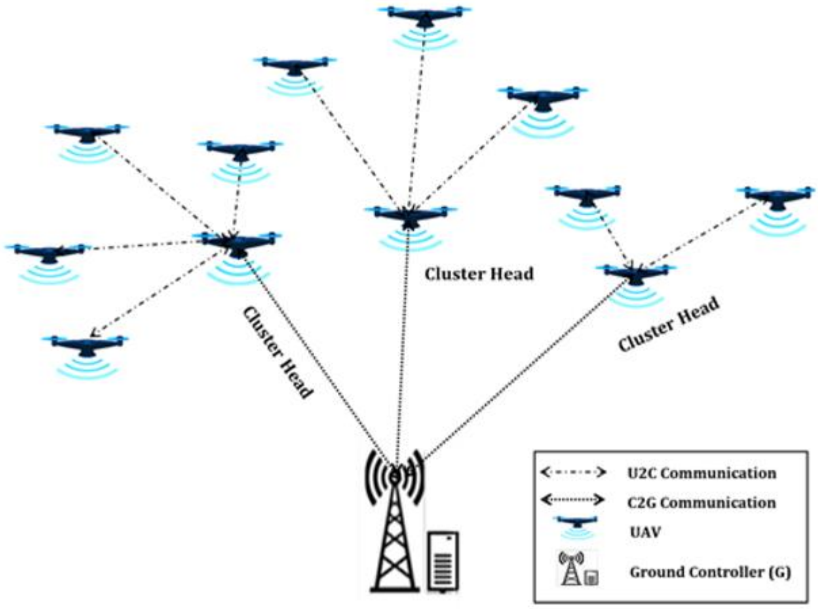

Figure 1. Communication architecture of UAV swarms (Asaamoning et al., 2021)

The proposed communication network model for UAV swarm cooperation and coordination during a wide-ranging mission is given in Figure 1. The computational system within the communication network of a UAV swarm is called a Networked Control System (NCS). The operating architecture of a general NCS consists of two basic systems. The first is a computational system that can collect data through sensors, make decisions and execute commands through actuators. The second is a network system that relies on network components, network standards and some basic protocols to communicate information (Asaamoning et al., 2021).

Swarm Intelligence

Swarm intelligence (SI) is the ability of a population of organisms, natural or artificial, to self-organize through collective behavior (Zhang et al., 2013). SI is the ability of a group of members to achieve a specific goal or task by exhibiting coordinated behavior based on simple rules. These rules regulate behaviors such as how swarm members interact with each other, the direction in which they move, and when they should stop. Each member can exhibit complex and organized behaviors, often sensitively responding only to nearby members, without explicit coordination. Often, these abilities observed in natural swarms can be reflected in various algorithms in computer science, AI, and engineering processes.

Throughout nature, different organisms often benefit from moving in swarms. Simple collective behavior models of group members demonstrate that they are sufficient to generate and provide group morphologies for uncomplicated partial interactions. Members collectively form groups capable of processing information and making decisions. Through shared information, a group can make better decisions than an individual member; this phenomenon is referred to as "collective intelligence" (Tang et al., 2021).

SI Algorithm

Rath et al (2020) emphasize that SI algorithms are used in many applications where real-time actions are processed efficiently, due to their dynamic properties. Idoko (2023) proposed a solution to the range anxiety experienced by electric car drivers with swarm intelligence algorithms. In this research, the author used PSO, a meta-heuristic optimization method, to optimize the travel path of electric vehicles between Bucharest and Cluj-Napoca.

During the mission of the UAV swarm, SI algorithms have been shown to be effective in some activities that require intelligence such as route planning, task allocation, obstacle avoidance, collision avoidance, target search, and communication (Bhagade & Puranik, 2012; Zhang & Duan, 2018). The algorithms used in the task optimization of UAV swarms involving intelligence are presented in Table 1.

Table 1. Algorithms for SI Problems

Algorithm Name	Type	Inspiration Source	Application Areas
Nearest Neighbor (NN)	Heuristic	Geometry	Logistics, Facility, Traveling Sales Problems (TSP)
Insertion Heuristic		Logistics	Production Planning, Location Selection
Swap Heuristic		Geometry, Sorting	Planning, Reversal
Clarke-Wright Savings		Logistics	Transportation, Distribution, Fleet Management
TSP Heuristics		Geometry	Travel Sales Problems, Logistics, Map Design
Genetic Algorithms (GA)	Meta-Heuristic	Genetic Evolution	Sorting, AI, Engineering, Optimization
Simulated Annealing		Statistical	Production Planning, Location Selection
Tabu Search (TS)		Local Search	Logistics, Sorting, Route Finding, Graph
ABC		Bee Behavior	Distributed Computing, Sorting, Logistics
Multi-Agent Systems (MAS)		Agent Systems	Game, Robotics, Distributed Systems
Firefly Swarm Algorithm		Insect Behavior	Distributed Computing, Sorting, AI
Artificial Fish Swarm Algorithm		Animal Behavior	
Cluster Search Algorithms		Clustering	Data Mining, Clustering, Grouping
Sparrow Search Algorithm		Bird Behavior	Optimization, Search
Ant Colony Optimization (ACO)	Optimization		Distributed Computing, Sorting, Logistics
PSO		Particle Behavior	Optimization, Production, Supply Chain
Cluster PSO (CPSO)		Based on PSO	Optimization, Clustering, Data Mining
A*		Geometry	Path Planning
Paxos Algorithm	Consensus		Load Balancing, Block chain
Raft Algorithm			

Table 1 shows the most widely used AI algorithms for improving SI. This table shows the names of the algorithms, their inspiration and the types of problems they are used to solve. SI algorithms are based on three approaches: heuristics, optimization and consensus, and aim to control the behavior of UAV swarms.

Path Planning via SI Algorithms in Task Optimization Process

Task Optimization is a concept that describes the process or method of an organization, an individual, or a system to perform specific objectives or tasks in the best possible way. The success of task optimization is determined by parameters such as the difficulty of the goal, environmental conditions, constraints, methods used, the number of members in the group, and coordination. Task optimization contributes to the efficient use of resources, process improvement, and minimizing losses. It has also become successful with the integration of next-generation information technologies such as machine learning, deep learning and AI to solve more complex problems. SI-based methods are commonly used in optimization problems. SI algorithms are often used in path planning processes.

Path planning involves determining the best route for an autonomous system from a starting point to one or more destination points. This process requires calculating the most efficient or safest route while taking into account factors such as environmental obstacles, system constraints, and objectives. SI algorithms can assist a group of autonomous entities, such as UAVs or autonomous vehicles, in coordinating their movements to find these routes.

While SI algorithms are used to ensure multiple autonomous systems work together simultaneously, path planning is used to ensure these autonomous systems move safely and effectively. When combined, SI algorithms and path planning can be applied in various fields, offering significant advantages. This approach is particularly beneficial in logistics, transportation, exploration, security, and more.

In their study, Akay and Karaboga (2012) introduced and applied a modified model of the ABC algorithm to effectively solve real parameter optimization problems. Lee et al. (2018) proposed the PSO algorithm for the target search task of a drone swarm. They demonstrated the practicality, accuracy, and robustness of their test simulation scenario. In Ekmen's study (2020), the task optimization of destroying a target with four drones was performed using ACO, PSO, and Krill Herd Optimization (KKO) algorithms. According to the research results, the objective function values for PSO, ACO, and KKO were 54.7, 73.83, and 69.41, respectively. Thus, the ranking of the best objective function value was PSO, KKO, and ACO. Saeed et al. (2022) obtained successful results in optimal road planning with 2D and 3D models of geographical environments with the ACO algorithm. They tried to optimize the ACO algorithm by measuring the estimated distances between the UAV and the obstacle to determine the new route during the flight. Especially in 2D environment, simulation results provided high efficiency.

The route planning and determination process is one of the most encountered problems in the task optimization process. Therefore, AI-supported search algorithms are often recommended (Giesbrecht, 2004). This problem needs to be handled with great care since it involves many static and dynamic factors such as distance, obstacles, error tolerance, and flight restrictions. Hoang et al. (2019) showed that by considering these factors and restructuring the PSO algorithm, the results of their application were more successful. In Wang et al.'s study (2023), the PSO algorithm was combined with the Enhanced SSA algorithm. In the application, they called PESSA method, under 10 basic functions, they achieved effective results in 3D route planning by comparing it with 12 other algorithms. In their TSP application, Wong et al. (2008) showed that the ABC algorithm outperformed GA, the Lin-Kernighan heuristic method, and other hybrid algorithms.

Method

In this study, swarm intelligence algorithms of the UAV swarm and ABC and PSO algorithms were used in path planning optimization. The task objective function of this path planning is to determine the best route and calculate the best distance. In this task, ten separate coordinate points and appropriate values for the parameters required for the algorithms to work were determined. The performances of the algorithms were compared by considering the objective function values obtained as a result of the application.

SI Algorithms

ABC Algorithm

This algorithm is a modelled approach inspired by the behavior of natural bee colonies during foraging in nature. Initially, the ABC algorithm was proposed as a SI approach to solve mathematical test function optimization problems using a unique neighborhood search mechanism (Choong et al., 2019). ABC is a computational process that starts by modelling a swarm of bees locating food sources in nature and communicating this to other swarm members. The model is a population-based algorithm in which the nectar quality, quantity and location of the source correspond to the optimum quality of the corresponding calculation.

In this algorithm, in the first step, the initial food source is determined. Bees start to move towards this food source, collecting information about the location of the food source, the amount of food available, and information about neighboring food sources, and then return to the hive. They then communicate the location and quantity of food to the other bees in the hive in a "dance" with a message. Each bee observes these dances and selects one of the food sources based on the information conveyed in the dances, then moves to that source. After selecting another neighboring source close to the food, they assess the amount of nectar. Food sources along the route are detected and replaced by other new locations discovered by the scout bees. At the end of this process, the best-found food source is recorded. The following Formula 1 is used to calculate the starting point of the foraging process of the bee swarm. In Formula 1, x_j^{min} and x_j^{max} are the initial values, in the mathematical model of the algorithm (Akay & Karaboga, 2012).

$$x_{ij} = x_j^{min} + rand(0,1) * (x_j^{max} - x_j^{min}) \quad (1)$$

$$v_{i,k} = x_{i,k} + \Phi_{i,k} * (x_{i,k} - x_{j,k}) \quad (2)$$

Each bee in the swarm produces a new position near its current position in Formula 2, where x_i is the initial position of the randomly selected bee and $\Phi_{i,k}$ is a randomly selected constant between (-1, 1). Then, the other bees evaluate the quantity information of nectar received from the scout bees and calculate the probability of nectar quantity according to Formula 3. Based on this calculation, they select a food source.

$$P_i = \frac{f_i}{\sum_j f_j} \quad (3)$$

At the end of each iteration, when a better source is calculated, the old source xi is discarded and replaced by this newly found food source. The scout bee then continues the calculation by discovering a new best food source with Formula 3 (Tsai et al., 2009; Akay & Karaboga, 2012).

PSO Algorithm

PSO is a method for optimizing nonlinear functions using particle swarm methodology (Kennedy & Eberhart, 1995). This method was put forward by observing that the movements of living creatures moving together for a purpose affect other individuals in the herd by communicating with other living creatures and the behaviors they determine in accordance with the purpose. PSO works to minimize a cost function. To model the swarm, each particle moves in a multidimensional space. In this algorithm, whose mathematical model for velocity and position calculations is given in Formulas 4 and 5, a particle is represented by the current position vector $x_n[t]$, the velocity vector $v_n[t]$, the desired position vector $x[t+1]$ and the next velocity vector $v_n[t+1]$. In the algorithm modelled with the help of these formulas, two vectors called the best local vector and the best global vector are calculated. The calculated size of these vectors depends on the size of the multidimensional space (Ekmen, 2020).

$$v_n\,[t+1] = wv_n[t] + c_1r_1(p(x) - x_n[t]) + c_2r_2(g(x) - x_n[t]) \tag{4}$$

$$x_n\,[t+1] = x_n[t] + v_n[t+1] \tag{5}$$

According to Formula 4, the velocity value of each particle is calculated for the next iteration (Hang et al., 2023). According to Formula 5, the positions of each particle are calculated for the next iteration. The main parameters of PSO are: size of the flock, number of iterations, acceleration coefficients and weight. In the process of each iteration, the new position of the particles in the swarm is tested with the objective function and its closeness to the solution is compared. The best state of the particle throughout the study is called 'pbest'. The position where the particles in the swarm are closest to the target throughout the study is called 'gbest'.

Scenario

It is assumed that the hardware and software characteristics of each UAV are the same. Variables such as inertia and torque values of the wing motors are added to the equation in the linear state space. It is assumed that the UAVs can communicate with each other within the swarm and are responsible for task distribution. Heuristic algorithms can give different results for each task definition and each re-route planning. The locations to be travelled in the algorithms may vary due to randomly selected parameter values. It is aimed to determine the shortest distance and optimum route starting from one unit and visiting other units once on the map formed by the units located at 10 coordinate points within the borders of the centre of Çorum province of Hitit University.

Coordinates of Academic Unit

The coordinate information of the names and addresses of the units of Hitit University located in Çorum Province are listed in Table 2. This information was obtained with Google Maps application.

Table 2. Coordinates of route points

Academic Units	Coordinates
Engineering Faculty (hitit_mf)	*(40.57044158989166, 34.982305542102566)*
Faculty of Theology (hitit_ilaf)	*(40.573342819527625, 34.984569326433615)*
Library (Hitit_lab)	*(40.57231599419518, 34.98657561872826)*
Rectorate (Hitit_rek)	*(40.57107726331548, 34.981071725847684)*
Faculty of Physical Education (hitit_besyo)	*(40.5688429641854, 34.98226248064795)*
Faculty of Arts and Sciences (hitit_fef)	*(40.56716352736973, 34.93347075523586)*
Hitit Research Laboratory (hitit_hb)	*(40.56845918300877, 34.9783109149586)*
Vocational School (hitit_myo)	*(40.55712101254516, 34.96893615751559)*
Health Sciences Faculty (hitit_sbf)	*(40.557292474174446, 34.9711289843594)*
Economics and Administrative Sciences (hitit_iibf)	*(40.53135121021779, 34.89877101655175)*

Hitit University units are marked on Google Maps and a sample route is shown in Figure 2. While these distances are measured in 10 meters within the campus, they reach kilometers with the addition of Hitit Fef and Hitit IIBF points. When these points are combined to form a route, its circumference is calculated as 18.81 km and its area is calculated as 12.15 km^2.

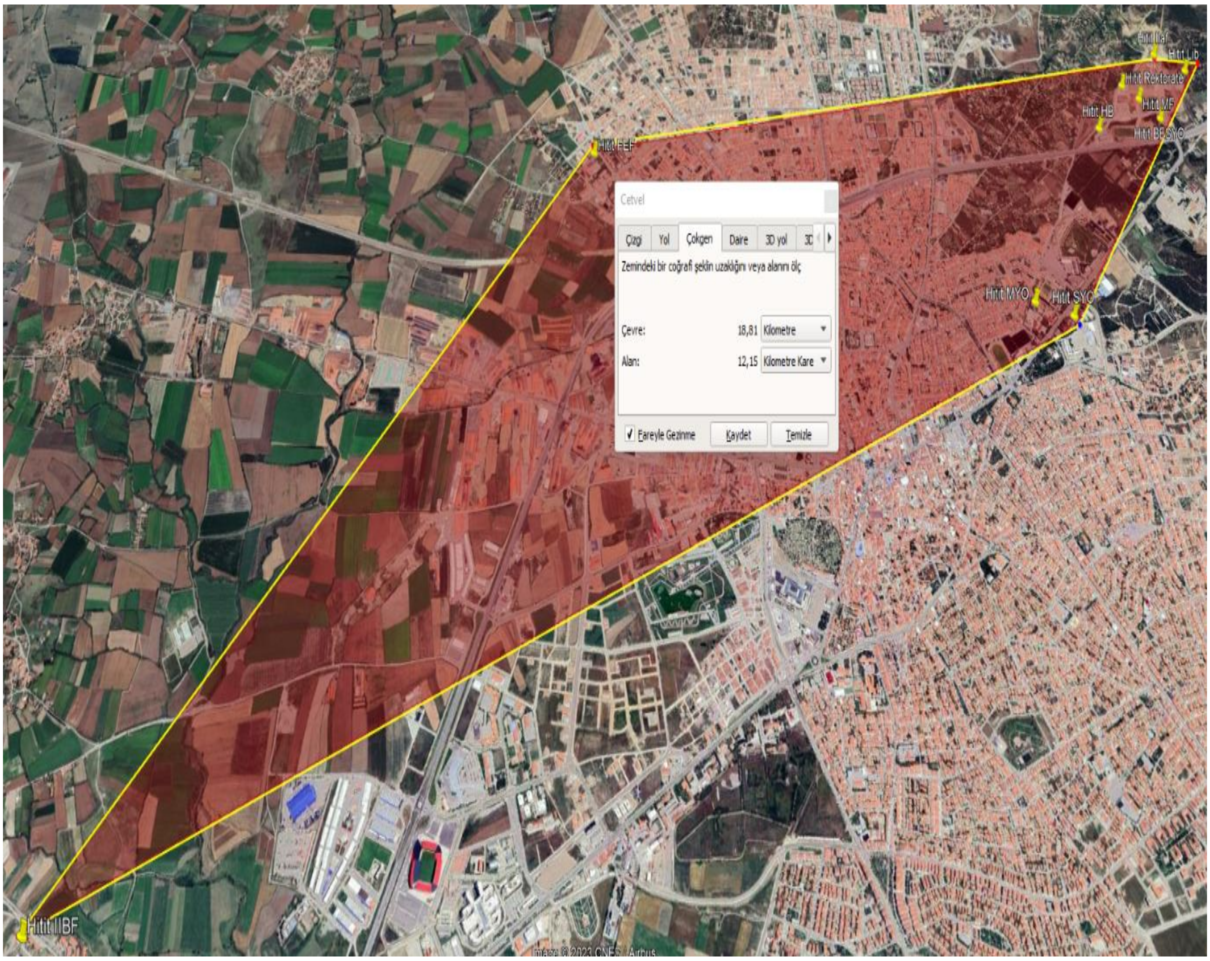

Figure 2. Representation of units on the map

Computational Parameters for the Algorithms

The computational parameters required for both algorithms are presented in Table 3. These values are set as standard and can be redefined according to criteria such as the number of elements in the swarm, UAV technical specifications, target distance and jump point.

Table 3. Parameters for the algorithms

Parameters for the ABC algorithm	Parameters for the PSO algorithm
number_of_bees = 100 # Swarm population	number_of_particles = 100 # Swarm population
n_iterations = 100 # Number of iterations	n_iterations = 100 # Number of iterations
flight_time = 40 # minutes	c1 = 0.5 # Personal best position weight
average_speed = 40 # km/h	c2 = 0.5 # Global best position weight
number_of_uavs = 20 # UAV population	w = 0.7 # Inertia weight
hop_node = 10 # Number of unit	hop_node = 10 # Number of unit

These parameters, coordinates of the units and mathematical models of the algorithms were taken from the scenario created within the scope of the application and coded in Python programming language. The codes are presented as computer algorithms in Algorithm 1 and Algorithm 2.

Python Pseudo Codes of the Scenario

Algorithm_1 shows the code steps that iteratively calculate the best path and distance within the scope of the application scenario with the ABC algorithm. The most important stage in this code is the stage where the ABC algorithm is applied in the light of the parameters.

Algorithm_1. Pseudo code of the ABC optimization algorithm.

1. Import necessary libraries:
   random, math and matplotlib libraries
2. Coordinates of academic units
   academic_units = {
   'hitit_mf': (34.982305542102566, 40.57044158989166),…
   }
3. Parameters for the ABC Algortihm:
   number_of_uavs, flight_time, average_speed, number_of_bees, num_of_iterations…
4. Calculate_distance
   def calculate_distance(…, …):
   x1, y1 = academic_units[…]
   x2, y2 = academic_units[…]
   return …
5. Calculate_total_distance.
   def calculate_total_distance(route, academic_units):
   total_distance = 0
   for i in range(len(route) - 1):
   total_distance += calculate_distance(route[i], route[i + 1])
   return total_distance.
6. Iteration for best_distace and best_route
   for _ in range(number_of_bees):
   bees_route
   route = list(academic_units.keys())
   random.shuffle(route)
   total_distance = calculate_total_distance(route, academic_units)
   bees_route.append((route, total_distance))
7. Sort bee tours by distance:
   bees_route.sort(key=lambda x: x[1])
8. Run the ABC algorithm
9. Print the best route and total distance
10. Display the plot using plt.show().
    Plot the route
    Plot academic units and the best route
    Plot the best distance/iteration graph

The pseudo code of the ABC optimisation of the scenario is shown in Algorithm_1. The algorithm is generally grouped in 10 stages. These stages, importing Python libraries, defining parameters. Calculating the distances, optimizing the result, implementing the ABC algorithm and displaying the outputs.

Algorithm_2. Pseudo code of the PSO optimization algorithm.

1. Import necessary libraries:
   random, numpy, math and matplotlib libraries
2. Coordinates of academic units
   academic_units = {
   'hitit_mf': (34.982305542102566, 40.57044158989166),…
   }
3. Parameters for the PSO Algortihm:
   number_of_uavs, flight_time, average_speed, number_of_particles, inertia_weight, p_best_position_weight, g_best_positions_weight, num_of_iterations…
4. Calculate distance
   total_distance = 0
   len(route) - 1):
   coord1 = coordinates[route[i]]
   coord2 = coordinates[route[i + 1]]
   distance = calculate_distance(particle, coordinates)
   total_distance += distance
   return total_distance
5. Calculate total distance.
   def calculate_total_distance(route, academic_units):
   total_distance = 0
   for i in range(len(route) - 1):
   total_distance += calculate_distance(route[i], route[i + 1])
   return total_distance.
6. Iteration for best_distace and best_route

normalized_distance = (global_best_distance - min_distance) / (max_distance - min_distance)
if global_best_distance < min_distance:
min_distance = global_best_distance
if global_best_distance > max_distance:
max_distance = global_best_distance

7. Sort particles tours by distance:
8. PSO initialization
   for iteration in range(n_iterations):
   for i in range(len(particles)):
   particle, distance = particles[i] …
9. Print the best route and total distance
10. Display the plot using plt.show().
    Plot the route
    Plot academic units and the best route
    Plot the best distance/iteration graph

The pseudo code of the PSO optimisation of the scenario is shown in Algorithm_2. The algorithm is generally grouped in 10 stages. These stages, importing Python libraries, Defining parameters. Calculating the distances, optimizing the result, implementing the PSO algorithm and displaying the outputs.

Results and Discussion

Firstly, in implementation, the positions of the UAV at the take-off point are created. The parameter values used in the PSO algorithm are; w=0.7 (usually chosen close to 1.), c_1=0.5 (a random value between 0 and 1), c_2=0.5 (a random value between 0 and 1). According to the ABC algorithm, the locations of the best nectar sources are initially randomized. The UAV check the nectar quantities of other UAVs and calculate which location they should go to for the next iteration. The proximity of each UAV to the target is determined according to the calculated new position objective function and it is decided whether it is suitable or not. This loop continues within itself until the determined iteration value. x_j^{min} (minimum value of initial coordinate) x_j^{max} (maximum value of initial coordinate).

```
---
ABC Alg_Best Route: ['hitit_hb', 'hitit_besyo', 'hitit_lib', 'hitit_ilaf', 'hitit_mf', 'hitit_rek', 'hitit_sbf', 'hitit_myo', 'hitit_fef', 'hitit_iibf']
ABC Alg_Best Total Distance: 0.12306030903721393 km
---
---
PSO Alg_Best Route: ['hitit_fef', 'hitit_iibf', 'hitit_myo', 'hitit_sbf', 'hitit_lib', 'hitit_mf', 'hitit_rek', 'hitit_hb', 'hitit_besyo', 'hitit_ilaf']
PSO Alg_Best Total Distance: 0.16771797460188603 km
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```

Figure 3. Best route information and distance values of ABC and PSO algorithms

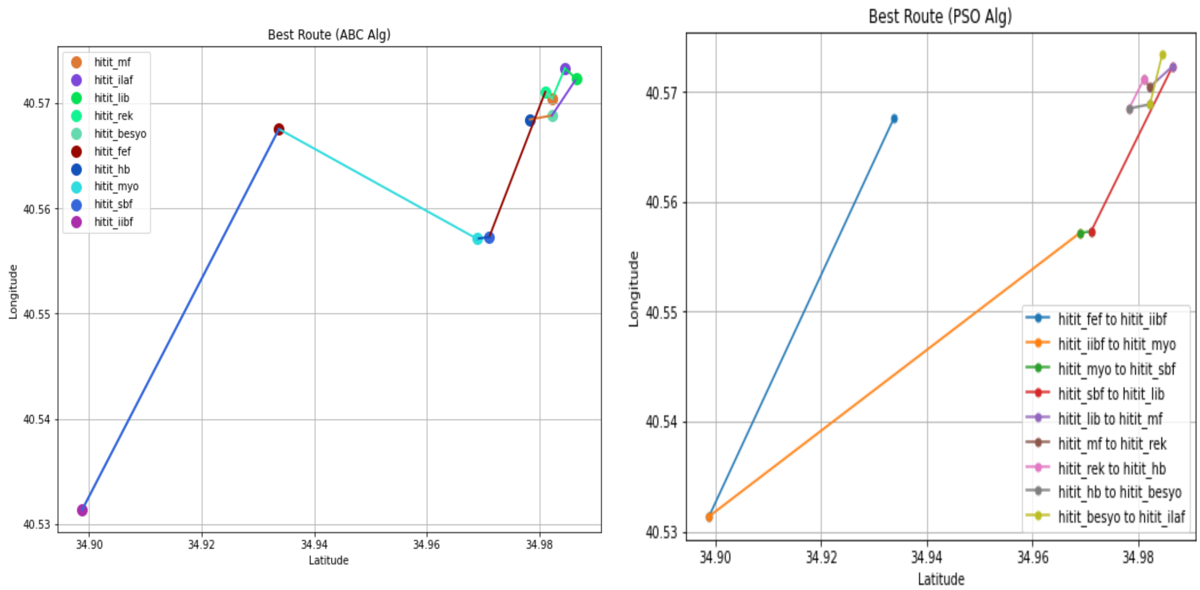

Figure 4. Best routes of ABC and PSO algorithms in route determination

When the Python codes were run, the results in Figure 3 were obtained. The best route estimation of the ABC algorithm started from Hitit Hubtuam (hitit_hb) and ended at Hitit Faculty of Economics and Administrative

Sciences (hitit_iibf). While the "Best Route Distance" value of the ABC algorithm was 0.123 km, the "Best Route Distance" value of the PSO algorithm was calculated as 0.167 km. The best route estimation of the PSO algorithm started from Hitit Faculty of Science and Literature (hitit_fef) and ended at Hitit Faculty of Theology (hitit_ilaf). These result values are the best values obtained at the end of the calculation by optimizing with the optimum number of iterations. The best path graph of the two algorithms calculated after each iteration is shown in Figure 4 and the best distance graph is shown in Figure 5.

Within the scope of task optimization and objective function, Figure 4 shows the best route determination of ABC and PSO algorithms. In this route determination process, the algorithms make calculations with the parameters given to them and determine this route by making a decision. Since the start and end points of the two algorithms are different, it is understood that they determine different routes.

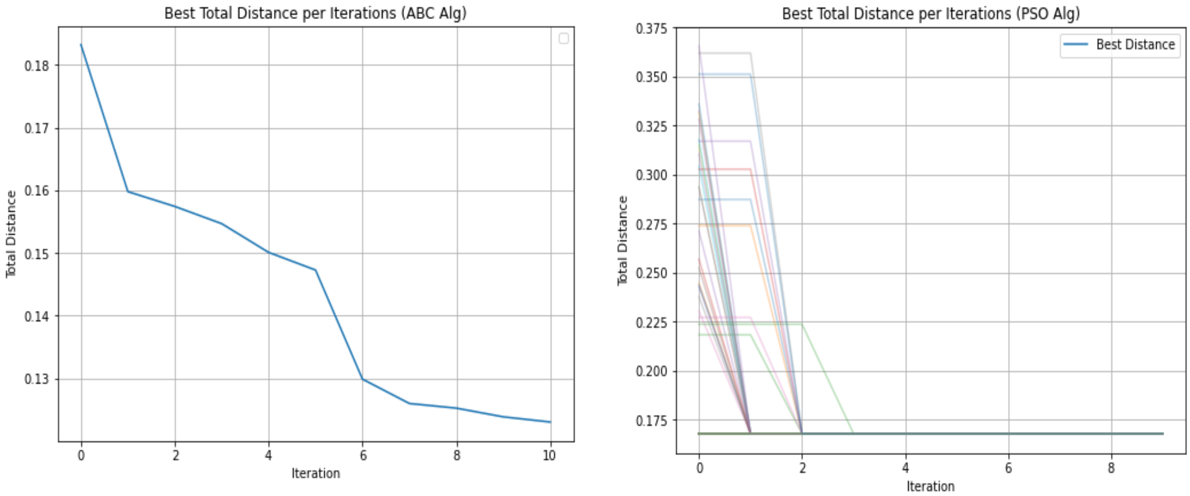

Figure 5. Best distance values with Iteration of ABC and PSO algorithms

The minimum distance calculation, which is the most important objective function of the task optimization, is shown in Figure 5. Both algorithms stabilized and calculated the distance after different iterations. Accordingly, the ABC algorithm determined the best distance as 0.123 km as a result of the 10th iteration. On the other hand, the PSO algorithm stabilized after the 3rd iteration and calculated the best distance as 0.167 km. It should be noted that these measurement values of the algorithms depend on the route determination, the swarm structure, the number of points and the distances between the units.

Conclusion

In this study, the objective functions of ABC and PSO algorithms, which are among the widely used SI algorithms for task optimization of UAV swarms, were calculated in a scenario developed over 10 different points. In the calculation of the best distance, which is one of the two important outputs of this scenario, the ABC algorithm produced approximately 25% more successful values than the PSO algorithm. In the determination of the optimal route, which is the other important output, the two algorithms determined different starting points. This difference is due to the parametric structures of the algorithms. In order to improve these values, both algorithms were subjected to iteration. As a result of different iterations, both algorithms became stable. This kind of research can be carried out with other swarm intelligence algorithms to reveal the similarities and differences between them. In addition, application results can be presented in a comparative manner to determine the most appropriate algorithm.

AI algorithms have become an important development tool for autonomous systems. In order for this tool to be used correctly and to provide successful results, it depends on the correct selection of the application-based algorithm, conditions and effective parameters. In addition, it should not be forgotten that constraints such as energy consumption, time, speed and information processing capacity, which are important for autonomous vehicles, should be included in the processes. In future studies, it is thought that new generation technologies such as blockchain will be effective in eliminating the constraints that prevent task optimization in UAV swarms.

Scientific Ethics Declaration

The author declares that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the author.

Acknowledgements or Notes

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