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Ant colony optimization for efficient distance and time optimization in swarm drone formation

Ronny Mardiyanto*[1], Andri Suhartono[2], Devy Kuswidiastuti[1], Heri Suryoatmojo[1]
Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia[1]
Institut Sains dan Teknologi Terpadu Surabaya, Indonesia[2]

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*Corresponding author.
Ronny Mardiyanto
E-mail address:
rony@ee.its.ac.id

Abstract

One of the challenges in swarm drone formation is achieving fast and effective formation with optimal distances. In this paper, we propose a swarm drone formation approach utilizing Ant Colony Optimization (ACO) for achieving it. We conducted simulations involving the formation of three or more drones, aiming to identify the best formation based on distance, acceleration, and time criteria. Simulation results demonstrate that formation time is significantly reduced when employing ACO optimization compared to non-optimized methods. Additionally, the optimized formations exhibit shorter inter-drone distances compared to non-optimized formations. By implementing this approach, swarm drone formations can be rapidly established with minimized distances, resulting in substantial battery savings. The simulation encompassed various patterns formed by 3, 5, 10, 15, 20, and 25 drones. The findings indicate that the approach can reduce formation time by varying degrees, ranging from 12% to 51%, across 66% of the conducted experiments, notably for patterns created with a substantial drone count. The degree of diversity observed among the proposed solutions reached 60%, with minimal variances of less than 1% for each.

1. Introduction

Drones are one of the most widely used types of unmanned aircraft. There are many sectors of work that use drones, such as the agricultural sector [1][2], mapping [3], photography [4], military [5], logistic [6], even drones are used for entertainment [7], that is drone formation shows. The drone formation show involves hundreds to thousands of drones. Several drones fly in certain formations, after a while the drones will move to form other formations. The drone formation show has been used as an opening for domestic and foreign events, such as at the opening of the 2018 Winter Olympics in Korea [8], and the opening of the Asian Games in Jakarta [9]. The number of drones is directly proportional to the number of formations; however, it becomes more complex as the number of drones used increases. In addition to configuring drone movements, the formation designer must perform calculations to ensure that the drones reach their designated destination points accurately. The determination of these destination points must be based on precise calculations and comparisons to minimize travel time, which is constrained by a limited display window. The task becomes increasingly challenging when dealing with formations of high complexity. More complex calculations carry a higher risk of errors, given the large number of calculated destination points, which involve various variables such as the initial drone positions, potential destination points, and drone characteristics, including acceleration, maximum speed, and the navigational path that accommodates gravitational acceleration effects. To mitigate errors, these calculations are best handled using specialized software programs. The developed software must be able to provide calculations and deliver results in the form of rapid and accurate points of interest. Determining the destination point through a comparison of each potential point of interest can yield correct results; however, it is time-consuming. Therefore, a faster and more precise method is required. The main objective of this paper is to overcome the drone formation problem, such as efficient distance and time optimization in swarm drone formation. The state of the art of this paper is that we employed the metaheuristic Ant Colony Optimization (ACO) approach to overcome it. The ACO method is anticipated to provide both destination points and optimal routes for each drone to efficiently form a formation with the shortest formation time[10].

Research on drone formations is commonly focused on the field of unmanned vehicles. The pursuit of faster drone formation is an advancement in UAV research aimed at determining the optimal path to reach waypoints. Previous studies have employed various algorithms for unmanned vehicles, with many of these algorithms relying on natural selection processes to generate solutions. Furthermore, ongoing efforts in algorithm development aim to identify the most effective path-finding methods. It is important to note that pathfinding for a single drone differs from pathfinding for multiple drones. This paper addresses scenarios involving multiple drones within a single display, where the coordinated movement of these drones simultaneously presents a challenge, with each drone potentially obstructing others in their pathfinding process.

In [10], two improved ant colony algorithms for drone path planning are discussed. The first algorithm is the Ant Colony Clustering algorithm, which draws its inspiration from the behavior of ant colonies when cleaning their nests. In the context of data analysis, this algorithm breaks down the Traveling Salesman Problem (TSP) into multiple smaller TSP problems, which are then solved individually. The second algorithm is an Adaptive Ant Colony Algorithm based on entropy, which is employed to quantify the uncertainty of information. Both the information-based update scheme and the path planning scheme can be adjusted based on the calculated information entropy value.

In [11], the Double-Ant Colony-based UAV path planning algorithm is discussed. This algorithm is an extension of the Ant Colony Optimization (ACO) approach, with the key distinction being the inclusion of an information exchange mechanism between the colonies. Both the Double-Ant Colony algorithm and an improved version of the Double-Ant Colony are subjected to simulation and evaluation using MATLAB. The simulated area measures 80x80 km and includes obstacles. In this simulation, proximity to obstacles is disregarded, and it is assumed that the UAV cannot traverse obstacles. The results of the simulation indicate that the Double-Ant Colony optimization converges by the 38th generation, while the improved Double-Ant Colony optimization converges by the 23rd generation.

A novel approach to ACO has been undertaken with the objective of reducing search times for multiple drones in the quest for locating missing targets under limited information conditions [12]. This innovative approach has been analyzed across six scenarios that were specifically designed to assess its effectiveness.

A scheme discussed in [13] enhances the conventional ant colony algorithm by introducing pseudo-random state transition rules and applying it to two-dimensional track planning for UAVs. The simulation results indicate that both the basic and improved ant colony algorithms can be employed in UAV path planning research. However, in two simulations conducted under identical conditions, the improved ant colony algorithm demonstrates a superior ability to search for an optimal track compared to the basic ant colony algorithm.

An improved ant colony algorithm is employed in [14] to address the issue of drone path planning within a specific region. Model calculations were performed using the map model of Puerto Rico. By introducing constraints into the state transition equation of the ant colony algorithm, the planning of multiple routes in a designated area is completed, yielding the optimal solution for the drone flight plan. The improved ant colony algorithm is utilized to minimize drone usage, considering drone losses and rescue operations.

A scheme discussed in [15] focuses on UAV 3D path planning using the ant colony algorithm. The model utilized southeastern Australia and identified wildfire hotspots. Monthly data from October 2019 to January 2020 was employed to evaluate the model. In the ant colony algorithm for three-dimensional space, longitude and latitude are discretized, and the optimal 3D path is visualized through simulation planning in MATLAB. The results demonstrate a reduction in model-generated errors.

The proposed scheme in [16] employs both the common grid method and the enhanced grid method to model and discretize actual irregular regions, respectively. The improved ant colony algorithm is then utilized to discover the shortest flight path connecting multiple discontinuous regions. The results of the MATLAB simulation analysis indicate that the flight path is shortened by approximately 4.46%, and the overall flight path is reduced after 7 iterations.

The improved ant colony algorithm in [17] utilizes the Tyson polygon structure to generate the initial solution and combines Jordan's approach with a safe distance consideration related to mountain barriers to enhance the efficiency of ant colony search. The results demonstrate that, under identical conditions, the path obtained using the improved ant colony algorithm is shorter, and the convergence efficiency is faster when a safety factor of 1 is applied.

The 3D track planning for electric power inspection based on improved ant colony optimization and the A* algorithm is discussed in [18]. The simulation results demonstrate that the improved ant colony optimization combined with the A* algorithm reduces the solution time for multirotor drone 3D track planning. In accordance with the minimal energy consumption track planning requirements, the simulation of the Goblet Straight-Line Single-Return Tower reveals that the solution time with the improved ant colony optimization-A* algorithm is 96.6% shorter than that with the A* algorithm.

Numerous aspects of drone dance performances serve as research areas for further development, with security being a critical concern. One of the primary concerns during a drone dance performance is the possibility of collisions between drones, necessitating specialized measures to prevent such incidents [19]. The operation of a group of drones requires them to adhere to predefined flight paths determined through a linear programming approach. The efficacy of the security system's development was assessed by successfully flying 30 drones during a performance.

The POS algorithm discussed in [20] led to the development of the SkySentry group flight control program. This program is capable of simulating group flight performance, previewing flight paths, inspecting path interleave status, conducting security isolation checks, and monitoring flight speed. The SkySentry system, once developed, effectively manages choreography, and orchestrates a light show involving 20 UAV swarms to prevent collisions.

To Achieve UAV Formation, several researches have been done. In [21], they conducted research on UAV formation simulation and evaluation technology by PID. It constructed the hardware-in-the-loop simulation and injected it into a UAV model. In [22], they made a UAV formation based on leader-follower. In [23], they made multi-UAV formation using distributed model predictive. In [24], they made multi-UAV formation using parameter optimization ADRC. In [25], they made multi-UAV formation using mesh network.

To overcome the drone formation problem due to its distance efficiency and time optimization, this paper proposes several contributions as follows:

- ACO is proposed for an efficient distance and time optimization in swarm drone formation. It works well for reducing the formation time of drones within 3-dimensional coordinates.
- Simulations involving the formation of three or more drones are conducted, aiming to identify the best formation based on distance and time criteria.
- Simulation results demonstrate that formation time is significantly reduced when employing ACO optimization compared to non-optimized methods. Additionally, the optimized formations exhibit shorter inter-drone distances compared to non-optimized formations. By implementing this approach, swarm drone formations can be rapidly established with minimized distances, resulting in substantial battery savings.

2. Research Method

In this chapter, we will explain the drone formations, drone flying area, the Optimization Algorithm and how to make the swarm drone formation become fast and efficient.

2.1 Accelerate Performing Drone Formation

The proposed drone formations are shown in Figure 1. With this numbering, the destination of each drone can be easily identified. Although the formation of the next drone can already be formed, the movements are very inefficient. To increase the efficiency of movements, the numbering must be updated.

With numbering that considers the efficiency of movement, the furthest distance traveled by drone number 2 and the shortest is still drone number 3, but the furthest movement is not as far as the movement made with the previous numbering. With a shorter distance, it will get a faster formation time if the vertical and horizontal velocities are always constant. This is certainly not in accordance with the conditions of the drone, each drone has a different horizontal acceleration and vertical acceleration value, a different horizontal maximum speed, and a different vertical maximum speed, and even has a different acceleration when flying vertically up and flying vertically down. Assuming the vertical downward flight acceleration is greater than the vertical upward flight acceleration, the numbering is slightly changed. With the existing assumptions, the formation time of the formation with this numbering will be slightly faster than the previous numbering.

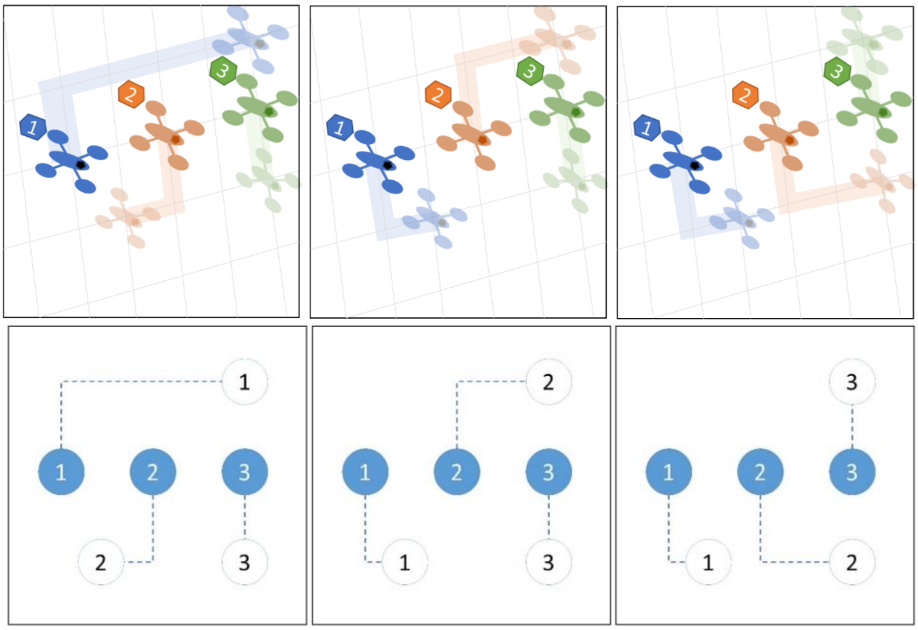


Figure 1. Drone Formations

Drone numbering by considering the distance and specifications of the drones can shorten the formation time, but in the actual formation of drones in the field, they move on a 3-dimensional plane, and the number of drones can be more than illustrated. The greater the number of drones used, more comparisons must be made, and when the pattern is more complex, the more complicated it will be in determining the correct numbering to shorten the formation time. In addition to the many errors, manual numbering when involving many drones or complicated patterns will take a long time to analyze, so other methods need to be used. For this reason, the ACO optimization method is used.

2.2 Drone Flying Area

The main difference between drones and other unmanned vehicles is their range. Drones are unmanned vehicles that explore the sky. The drone can do free movement in the air, forward-backward movement, left-right, up-down, the drone can be operated on all three Cartesian coordinate axes (x, y, and z axes). Rotational movements can also be performed on all three axes (roll, pitch, and yaw). With movement in all three Cartesian axes and the cruising area is air, it can be said that drones have the widest cruising area when compared to other unmanned vehicles. However, the widest cruising/flying area does not mean that it is not limited. The drone's flying area is limited to the drone controller's transmission range. In this paper, the controller transmission used is a wifi router so that the drone's flying radius is limited to 100 meters with the ground station as the center.

In its application, the drone is always equipped with a GPS to determine the position of latitude and longitude and is equipped with a barometer to get the altitude. The longitude, latitude, and altitude values given are not always correct, sometimes they are several meters apart from the original position. The difference in value with the original position is caused by the accuracy of the GPS module and barometer module used. To overcome collisions caused by position reading errors, the distance between drones is limited. The minimum radius between drones is set at 5 meters, this figure is taken considering the accuracy of the GPS module used.

2.3 Optimization Algorithm Development

The optimization algorithm used to accelerate the forming of the drones' formations is ACO. To apply ACO to the formation of this drone formation, it is necessary to determine the waypoints that become the center of the ant colony and the waypoints that become food sources. In this drone formation, the number of food sources is not only one, but several food sources can also be visited by various routes. Before the destination food source or destination waypoint is determined, all the waypoints to be addressed are referred to as destination waypoint candidates. Each food source can be visited in various ways and can also be visited by any ant colony, but if the food source has been controlled by one ant colony, then other ant colonies cannot go to that food source.

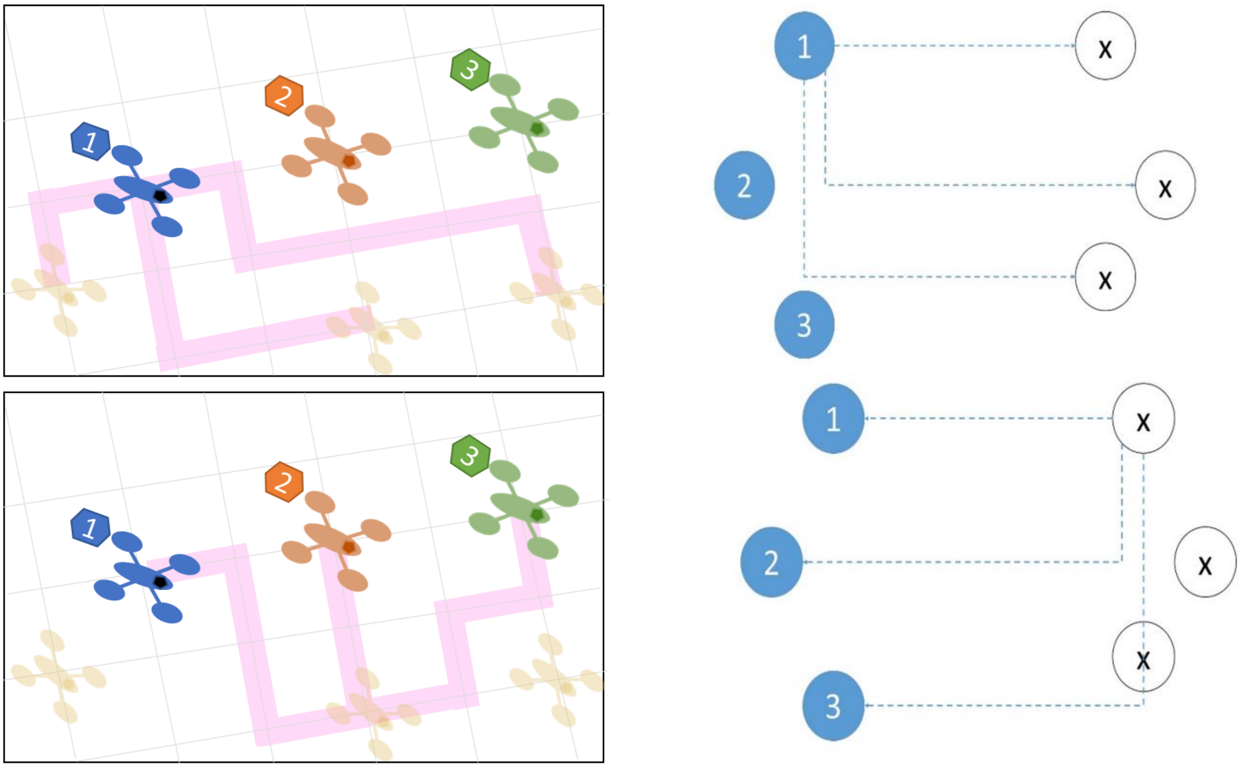


Figure 2. Initial Waypoint and Destination Waypoint Candidates

In its realization, there are two possible scenarios to be realized in determining the initial waypoint and destination waypoint candidates, namely current positions as the initial waypoints and positions in subsequent formations as the destination waypoint candidates, or the second scenario is the positions in the next formation as the initial waypoints and current pattern points as the destination waypoint candidates.

These two scenarios can have different or same results depending on the waypoint determination used. When using the first scenario, it tends to position the drone with number 1 being the first colony to conduct inspections. This makes the UAV with the last serial number get a destination candidate waypoint that was not selected by other origin waypoints. In the second scenario, the tendency to carry out inspections based on the sequence will be slightly reduced due to the absence of proper numbering, so it can be done using position order. The position of the waypoint in the next formation that has the furthest distance from the current waypoint position can be the first to be analyzed because filling in the parts that are farther away first can minimize the obstacles that occur in the formation. Therefore, the determination of the initial waypoint and destination waypoint candidate used the second scenario. The initial waypoint and destination waypoint candidate is shown in Figure 2.

Before starting the ACO process it is necessary to declare the related variables. The related variables that need to be adjusted are the main ACO variables including the number of ants, the initial value of the pheromone, the evaporation value of the pheromone, and the limit on the number of iterations.

2.3.1 Number of Ants

When making a formation change, every drone that will make a move will be faced with several choices of possible paths to go through. In ACO, not all paths will be checked. The path will be chosen at random for the number of ants used. In this process, the number of ants used is based on the number of original waypoints, which is 3 times the number of waypoints.

2.3.2 Pheromone

The amount of pheromone value when the ACO process is started is made the same for each path. The set value is 2 for all paths. With the same value at this start, then all paths have an equal chance of being selected in the search. This process is like the condition when the ant colony does not yet know the way to the food source, all routes will be explored.

2.3.3 Number of Repetitions

The ant's journey cycle is carried out several times, the travel path taken by the ant can be different or the same depending on the random value that will be used to choose the path that the ant must pass. In the second iteration, the path selection is no longer balanced, the pheromone value of each route is no longer the same because there is a path that has been passed by the ants which results in a higher pheromone value on that path. Paths with higher pheromone values have a higher chance of being selected for ants to traverse. If in the second iteration a path that is shorter than the shortest path in the first search is found, the pheromone values of the two paths may be approaching each other, but in the next iteration when the ants take the two shortest routes, the pheromones on the second shortest route will become more concentrated. With the concept of pheromones and repeated many times, in the end, all ants in the colony will pass the same route, that will be the chosen solution. The selected solution can also be determined if the candidate solution has a fitness value that reaches the specified limit. If the fitness value is not reached, or the ant colony does not choose the same route, an unlimited number of loops will occur, therefore a limit on the number of repetitions must be determined. When the iteration has reached its limit, but the fitness value has not reached the specified value and the ant colony is not on the same path, one path with the highest pheromone value and a fitness value not equal to zero will be chosen as the final solution. By default, the highest number of iterations used is 10 iterations. The number of 10 iterations is determined based on trials.

Besides the main variable, there is a function that will be used in the ACO process in this paper, the function that has been mentioned previously is the fitness function. This function is found in several optimization methods based on genetic methods. This function can help speed up the determination of the solution because the result of this fitness function is the quality value of the candidate solution. The fitness function is written in an equation containing the variables that affect the quality of the solution. If the value of the fitness function reaches the specified limit, then the candidate solution can be directly selected as the final solution. In its application to accelerate the forming of drone formations, the variable that plays a role in determining quality is the length of time taken ($t_{i,n}$) and the number of flight acceleration which is divided into number of positive vertical acceleration (n_{av}^{+}), number of negative vertical acceleration (n_{av}^{-}), and number of horizontal acceleration (n_{ah}), but there are still other factors that affect the quality of the solution, namely the position of the drone to the control center. The shortest possible flight distance will be useless if the drone flies outside its flying area (p=0, if it flies outside flying area, p=1 if flies inside flying area) which causes a communication breakdown between the control center and the drone so that the flying radius greatly affects the quality of the solution. The selected fitness function equation is shown in Equation 1.

$$fitness = \frac{p}{(t_u - t_{i,n} + 1)\left(\frac{a_{max} - a_{v+}}{n_{av}^{+} + 1} + \frac{a_{max} - a_{v-}}{n_{av}^{-} + 1} + \frac{a_{max} - a_h n_{ah}}{n_{ah} + 1}\right)} \quad (1)$$

The smaller the resulting fitness value, the higher the resulting quality. If the fitness value is lower than or equal to 0, then the solution cannot be realized and a new solution is needed. a_{max} is the maximum acceleration that can be achieved by the drone, a_{v+}, a_{v-}, and a_h are vertical and horizontal acceleration of the drone, considering both positive and negative vertical and horizontal are usually have different accelerations. In this paper $a_{max} = 5$, $a_{v+} = 4$, $a_{v-} = 4{,}2$, and $a_h = 4.3$.

The data from the drones taken before entering the ACO process include the number of drones that play a role, the x, y, and z coordinates of each drone at this time, the x, y, and z coordinates of the drone to be targeted, the speed and acceleration of the drone to all coordinates. This ACO process will result in a change in the destination point of each drone, and it will also produce the best route that will be traversed by the drone.

One ACO process is used to determine the solution for moving from one formation to another. Therefore, if in a drone formation show there are 10 formations to be formed, the ACO process is run 9 times to determine the fastest formation path. The flow of one ACO process in the process of selecting the best waypoints and routes is described in Figure 3.

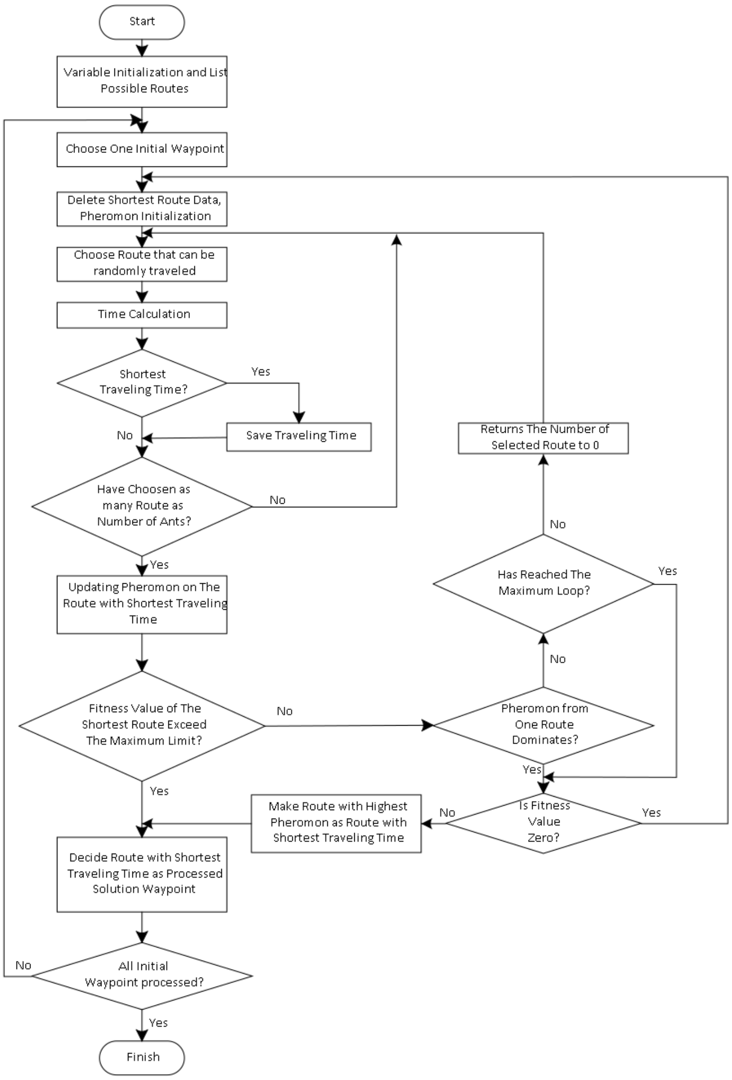


Figure 3. ACO Process of Selecting the Best Waypoints and Routes Flowchart

The pheromone evaporation on each route can be assessed by using Equation 2:

$$\sigma_{i,j,k} \leftarrow (1-e)\sigma_{i,j,k} \tag{2}$$

In the forming this formation an evaporation rate of 30% is used.
After evaporation, the best route would be to add pheromones, it can be seen in Equation 3 and Equation 4:

$$\sigma_{i,j,k} \leftarrow \sigma_{i,j,k} + \Delta\sigma \tag{3}$$

$$\Delta\sigma = 7\left(\frac{t_{mf} - t_{i,n}}{t_{mf}}\right) \tag{4}$$

Seven is a constant that represents the full pheromone level of an ant. If a route gets an additional 7 points of pheromones, the ants stay on the route because the length of the route is 0. The longer the route taken by the ants, the more scattered pheromone levels will be on the route and result in reduced levels of pheromone added to the route.

If the transfer time is longer than the specified transfer time, the route is not recommended and the pheromone aroma will be considered to have evaporated, resulting in a reduction in pheromone levels.

The fitness function of the best route will be compared with the limit of the fitness function. This comparison becomes one of the determinations of the solution of the processed waypoints. The maximum limit for the value of the fitness function in forming this drone formation is set at a value of 0.2. This 0.2 value is taken by considering if the difference between the travel time of the best route and the travel time using the main movement model (t_u) is not more than 4 seconds, total number for acceleration is not more than 15 times and the route is not off track then this best route can be directly taken as a solution.

After determining the formation to be displayed and performing ACO calculations, the drone formation can be done. The following are the stages of forming drone formation which is described in Figure 4.

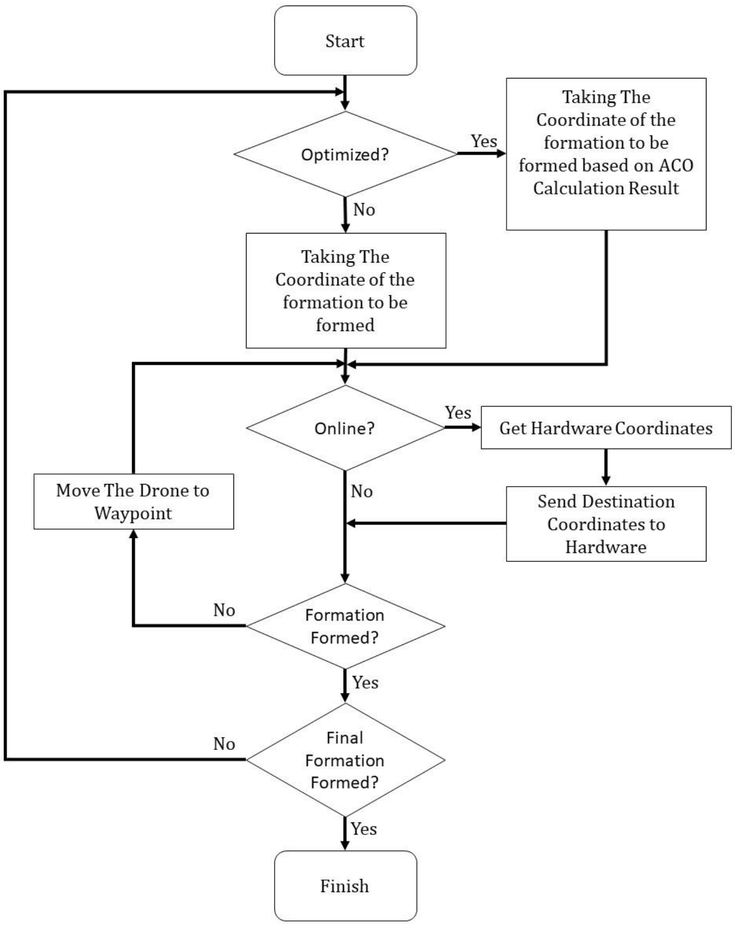


Figure 4. Stages of Forming Drone Formation Flowchart

3. Results and Discussion

Trials in the form of simulations were carried out in several stages to see the effect of optimization techniques on the forming drone formations. The trial was carried out as many as 15 trial models where trial 1 to trial 6 formed 2 simple formations, trial 7 formed 3 simple continuous formations, trial 8 formed 4 continuous simple formations, and trial 9 formed 5 continuous simple formations. , trials 10 to 15 formed 2 complex formations. The initial positions of drones are (0,5,5), (15,5,5), and (30,5,5) with the destination are (10,-5,0), (30,15,5), and (30,-5,0).

The first stage of the trial results will show the results of simulation trials which include changes of formation time between formation involving optimization methods and formation without optimization methods, it is shown in Figure 5. From the experimental results, the ACO calculation process time is quite short. Of all the calculations performed none reached the calculation for 1 second. This means that ACO can find a solution quickly, however, the more drones involved, the longer the calculation time. When forming a simple formation, the results of the optimization method do not play much of a role, from 6 trials with 2 simple formations. Optimization methods play a significant role when it comes to formation formations in complex formations. Although the results of the optimization method did not significantly reduce the formation time, it can be seen in trials 7 to 9 when there are many formations in one formation row, the effect of the optimization method becomes quite large in reducing the formation time.

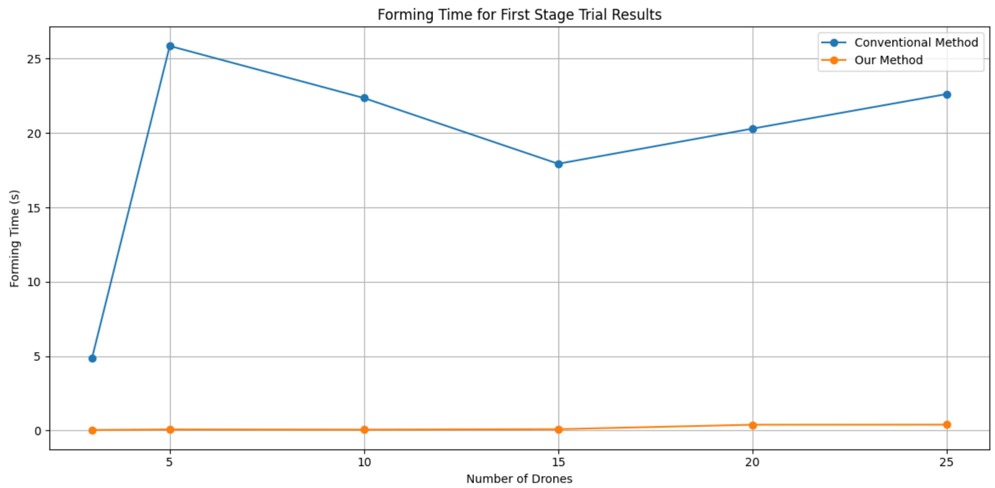


Figure 5. First Stage Trial Results

The second stage of the trial results will display the results of a simulation test that compares the total distance traveled between formation without using the optimization method and the formation using the optimization method, it is shown in Figure 6.

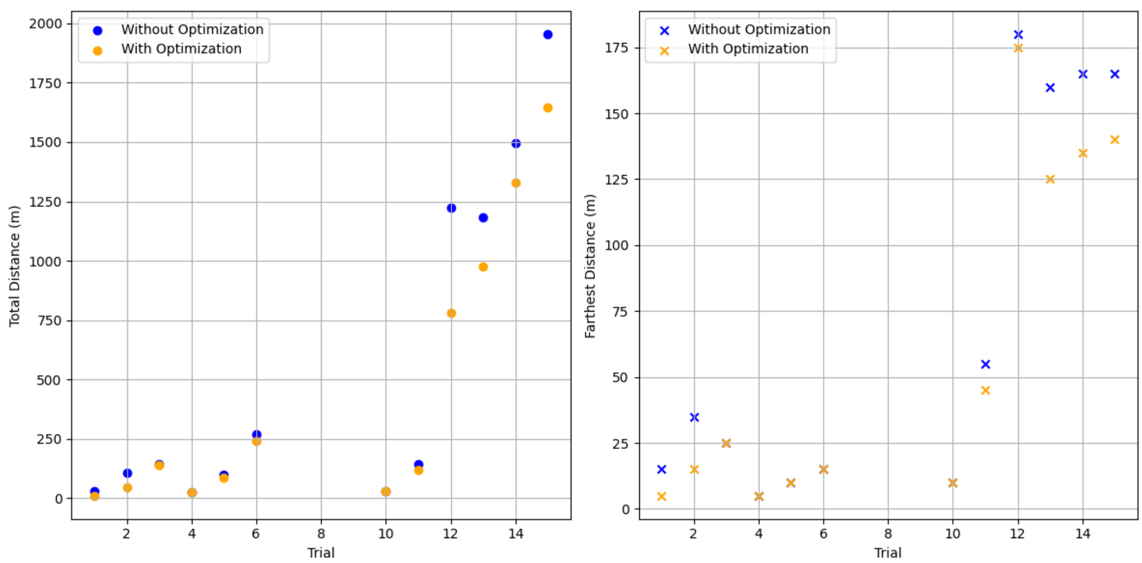


Figure 6. Second Stage Trial Results

From the experimental results by using the optimization method, the route selection based on distance also becomes better. All routes selected using the optimization method have a total distance that is smaller than or equal to the route selected using numbering. Most of the routes chosen by the optimization method have the same length as the numbering method when the formation built is simple or involves a/ small number of drones. The furthest distance obtained will also certainly not be more than the farthest distance without an optimization method because the furthest distance becomes the benchmark in determining the formation time.

The third stage of the trial results will show the diversity of the solutions obtained when forming the formation using the optimization method, it is shown in Table 1 and Table 2. This trial was carried out by repeating the formations using 5 drone units as in trial 2 to see the diversity of solutions in the forming of a simple formation and repeating the formations using 10 drone units as in trial 12 to see the diversity of solutions in the forming of a complex formation.

Table 1. Experiment using 5 Drones and 2 Simple Formations

Solution	Calculation Time (ms)	Total Displacement (m)	Farthest Distance (m)	Flight Time (s)	Movement Variation
1	37,622	55	15	9,057	A
2	36,251	55	15	6,875	B
3	36,491	55	15	7,115	B
4	35,294	45	15	8,527	A
5	37,274	55	15	9,587	C

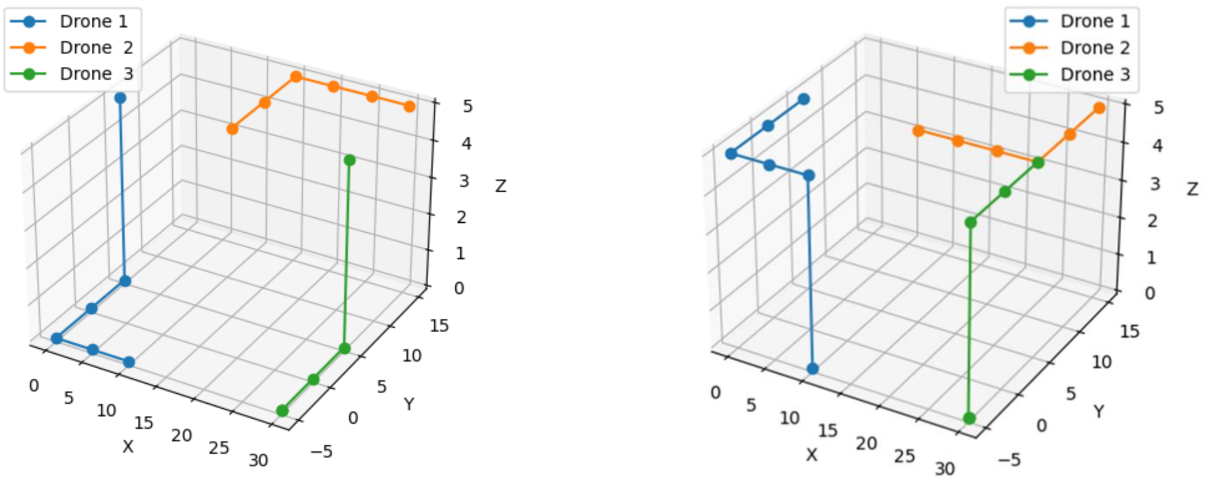
Table 2. Experiment using 10 Drones and 2 Complex Formations

Solution	Calculation Time (ms)	Total Displacement (m)	Farthest Distance (m)	Flight Time (s)	Movement Variation
1	94,699	720	160	30,041	A
2	90,218	730	160	31,102	B
3	87,274	740	160	31,921	C
4	93,912	720	155	29,562	D
5	88,285	730	155	30,628	E

In Table 2, the solutions issued are quite diverse. In trials with 5 drone units forming 2 simple formations, from 5 times the solution sought, there are 3 different combinations of routes. The more the number of drones involved, the possibility of route combinations or the level of diversity will increase, as happened in the search for a solution with 10 drone units forming 2 complex formations, out of 5 solution searches there were 5 different route combinations.

The comparison of the trajectory route between conventional method and ACO is shown in Figure 7. First, drones start from (0,0,5), (15,5,5), and (30,5,5), destination points are (10,-5,0), (30,15,5), and (30,-5,0). Drones move along the routes that are created using the conventional method (Figure 7.a) and ACO (Figure 7.b).

During experiments, the environmental influences were still considered stable and only considered the gravitational acceleration which had influenced the vertical acceleration value in the equation for finding the suitability value.



(a) (b)

Figure 7. Example of Trajectory Route, (a) Conventional Method, (b) using ACO

4. Conclusion

Overall, it can be concluded that ACO has succeeded in accelerating the forming of the swarm drone formation. 66% of the forming drone formation experiments showed an acceleration of forming drone formation of more than 1 second, while 34% of the other experiments had an acceleration of less than 1 second. The effect of the acceleration of forming drone formation also varies, ranging from 12% to 51% of the acceleration of forming simple drone formation. The effect of acceleration is more visible in the forming complex formations, where complex formations are formations that involve many drones and have complex formations.

The ACO calculation process is quite fast because it almost does not affect the total flying time of the drone, but the calculation time continues to increase as the number of drones used increases. From the experiments, the calculation time for the optimization is above 100 ms when more than 10 drones are involved. So, it would be better if the process of finding a solution using ACO was done before the show started.

In addition to shortening the travel time, this optimization technique also provides a choice of routes with shorter shifts than routes without optimization techniques. 66% of the experiments carried out succeeded in obtaining a shorter transfer route with a range of 3% to 67% of the specified route without optimization techniques.

The solution produced from ACO is not the most optimal solution, this can be seen from the high level of diversity, which is around 60% to 100%. However, the solution obtained is not far from the optimal solution, this can be seen from the travel time that is close to each other even though the routes taken are different, the difference in travel time for each solution is less than 1%.

The process of forming a swarm drone formation has been successfully carried out. There are 40 documented experiments and dozens of undocumented experiments that have succeeded in establishing a drone swarm formation without any problems with collisions between drones, or failure due to an error in the division of tasks.

Notation

p : numerator value, p=1 if the drone is within control range, p=0 if the drone is out of control range,
t_u : travel time if the UAV uses the main movement model,
$t_{i,n}$: travel time of the i-th UAV to reach the formation of n-th drone,
a_{max} : maximum acceleration of UAVs,
a_{v+}, a_{v-}, a_h : Positive vertical acceleration, negative vertical acceleration, and horizontal acceleration of the UAV,
$n_{av}^{+}, n_{av}^{-}, n_{ah}$: The total number of positive vertical accelerations, negative vertical accelerations, and horizontal accelerations that occur during the formation process.
$t_{i,n}$: travel time of the i-th UAV to reach the formation of n-th drone,
$\sigma_{i,j,k}$: pheromone levels from the i-th origin waypoint to the j-th destination waypoint with the k-th route,
e : Evaporation rate.
$\Delta\sigma$: pheromone levels added on the best route,
t_{mf} : longest shift time allowed in the show.

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