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ENHANCING ANT COLONY OPTIMIZATION WITH GENETIC ALGORITHM AND 3-OPT FOR MULTIPLE DRONE SPRAYING PATH PLANNING IN PRECISION AGRICULTURE

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Abstract. Efficient and environmentally responsible pesticide application is a major challenge in precision agriculture. Excessive pesticide use in conventional farming increases costs, harms the environment, and poses health risks. Recent advancements in unmanned aerial vehicles (UAVs) or drones have enabled targeted spraying, yet optimizing multiple-drone route planning and task allocation remains complex due to dynamic field conditions and limited drone capacity. To address this gap, this study proposes a hybrid optimization approach that integrates Ant Colony Optimization (ACO), Genetic Algorithm (GA), and 3Opt to generate efficient flight routes for multiple sprayer drones based on plant health levels. In this framework, ACO assigns drones to target points, GA automatically tunes key ACO parameters, and 3Opt enhances route efficiency through local optimization. Experimental results show that GA effectively automates the tuning of four key ACO parameters and that drone capacity significantly affects route length. The integration of GA, ACO and 3Opt further reduces total route length, achieving up to 13.6% improvement in efficiency compared to traditional ACO. These findings demonstrate the potential of the proposed method to enhance route efficiency, reduce energy consumption, shorter mission completion time and offers a practical solution for improving the performance and sustainability of multiple-drone spraying operations.

Keywords: ant colony optimization, genetic algorithm, 3Opt, agriculture, flight route, multiple drones, optimization.

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1. Introduction

The use of pesticides can no longer be ruled out and has a vital role in agriculture because it can improve plant health and increase crop yields. If agriculture did not use pesticides, fruit production would fall by 78%, vegetables would drop by 54%, and cereals would fall by 32% (Tudi et al., 2021). The use of pesticides can cause chemical residues that can impact human health through food and have the potential to pollute the environment (Liu et al., 2015; Scholtz & Bidleman, 2007).

Drone technology may be used in the agriculture industry to mitigate environmental contamination caused by pesticide usage and enhance crop yields. Initially, drones might be used to oversee the condition of plants by using payloads in the shape of multispectral cameras (Hafeez et al., 2022; Neupane & Baysal-Gurel, 2021; Reinecke & Prinsloo, 2017). Cameras installed on drones produce more analytical and practical image data compared to satellite data (Bollas et al., 2021).

Furthermore, drones may serve the purpose of applying pesticides by spraying (Hafeez et al., 2022; Sharma & Dadheech, 2023). Currently, pesticide spraying is mostly carried out manually, with the operator personally carrying a tank containing liquid pesticide. According to the World Health Organization (WHO), this type of spraying results in several adverse effects (Mogili & Deepak, 2018). Apart from that, if it is related to environmental pollution, the manual spraying method does not pay attention to the dose of pesticide given to plants, so if too much pesticide is given, it increases the level of environmental pollution.

The use of drones for pesticide application provides more benefits when employed over expansive agricultural land. Using drones has many advantages, including efficiency in the time used (Priandana et al., 2023a) and a lighter workload for operators. The utilization of multiple drones can further augment this benefit, owing to the constrained capacity of battery resources. The operational duration of a drone is contingent upon the battery's capacity (Boukoberine et al., 2019; Townsend et al., 2020), thus, pesticide spraying with many drones is more efficient and effective.

The use of several drone units in one mission is closely related to planning the flight routes of these drones. In the field of smart agriculture, the use of Artificial Intelligence (AI) is possible to be applied (Ayundyahrini et al., 2023; Sharma & Dadheech, 2023), one of which is to increase operational efficiency (Huerta-Soto et al., 2023) in this problem. Planning drone flight routes can be done using the Multiple Traveling Salesman Problem (MTSP) concept, which is a development of the Traveling Salesman Problem (TSP) (Nisrina et al., 2022; Shuai et al., 2019). Many salesmen are involved in visiting several points at once (Nisrina et al., 2022), taking into account the distance to be as small as possible (Cheikhrouhou & Khoufi, 2021; Priandana et al., 2023b). Several algorithms can be used to solve MTSP cases, including Genetic Algorithms (Al-Omeer & Ahmed, 2019; Wang et al., 2020; Yuan et al., 2013), Artificial Bee Colony (Dong et al., 2019; Pandiri & Singh, 2018; Venkatesh & Singh, 2015), Particle Swarm Optimization (Asma & Sadok, 2019; Wei et al., 2020), and Tabu Search (Farizal et al., 2022; Lee et al., 2020; Venkatachalam et al., 2018). Apart from only using one type of algorithm, several methods have also been developed and combined to obtain a more optimal solution method, including Hybrid PSO-ACO (Elloumi et al., 2014), MOEA/D-ACO (Ke et al., 2013), Hybrid AC-PGA (Jiang et al., 2020) and Hybrid Memetic-ACO (Decerle et al., 2019).

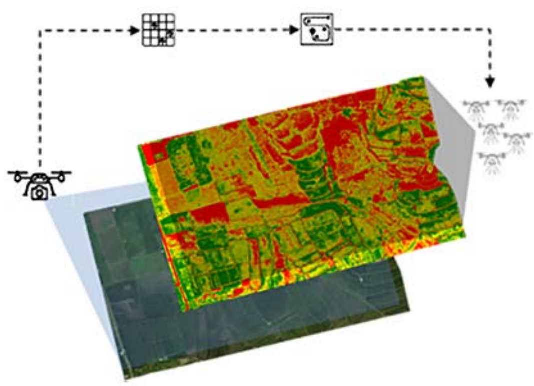
In this research, a drone flight route planning strategy was developed using the Ant Colony Optimization (ACO) algorithm, which is widely used in swarm intelligence and optimization studies (Grace et al., 2023; Hardhienata et al., 2024; Huang et al., 2020). However, a significant research gap remains regarding the automatic determination of optimal ACO parameters. Existing studies (Pranaswi et al., 2024) show that while UAV-based spraying systems enhance deposition and efficiency, the planning of flight routes and algorithmic parameter optimisation remains under-explored. Moreover, comparative work (Hiremath et al., 2024) has demonstrated that although drone sprayers improve speed and water/labour efficiency over conventional methods, the process still relies on manual tuning and route planning, reducing scalability. Finally, comprehensive reviews (Meesaragandla et al., 2024) point out that while detection and application technologies with drones are advancing, the integration of multiple-drone route planning, health-based plant variation, and algorithmic optimisation (ACO+GA+3Opt) is rarely addressed. To address these research gaps, this study proposes a multiple-drone flight route planning strategy based on plant health levels, integrating the ACO algorithm with Genetic Algorithm (GA) parameter optimisation and final refinement using the 3Opt algorithm. The GA is employed to automatically search for the optimal ACO parameter set, thereby enhancing route optimisation efficiency, while 3Opt further minimises route length. The primary objective of this research is to develop an intelligent, adaptive, and efficient route-planning framework for agricultural drones that reduces processing time, minimises human intervention, and ensures environmentally-responsible pesticide application. Ultimately, by implementing this system, pollution and environmental degradation caused by excessive pesticide use can be reduced, while improving farmers' productivity and land management efficiency.

2. Method

In general, the ecosystem from this research can be illustrated in Figure 1, where there is a drone with a multispectral camera load that is used to monitor plant health and carry out aerial photography (mapping) of agricultural land objects. The image from drone mapping is then subjected to several processing processes to produce points containing information on plant health levels. After obtaining this data, several drone spray-flying routes at these points were then planned. The spray drone then uses the resulting route to carry out spraying missions based on the level of plant health and the distance between points.

The flight route planning for several drones is based on coordinate point data and plant health levels that already exist in the dataset. Flight routes are designed using several algorithms, namely:

- Ant Colony Optimization (ACO) plays a role in allocating drones to target points. In this heuristic method, the initial solution is initialized randomly and then updated as the iteration progresses (Sharma et al., 2023). This optimization technique repeatedly applies new information obtained to create an optimal solution (Nayyar et al., 2019). Setting initial parameters is very important for the success of the search process in this method (Vashishtha et al., 2013).
- Genetic Algorithm (GA) is used to optimize the parameters of the ACO algorithm (for hyper-parameter tuning). Several factors influence the performance of



Note: It starts with collecting agricultural land imagery, analyzing plant health levels, planning flight routes, and ends with spraying operations using multiple spraying drones.

Figure 1. General description of the research ecosystem

GA, including population size, crossover probability, mutation probability (Zhang et al., 2008, 2010), and number of iterations (Younas et al., 2011). The population size in GA also affects the accuracy and speed of finding the optimal solution (Roeva et al., 2015).
- 3Opt, used to optimize routes generated by the ACO+GA algorithm (local optimization). The working principle of this algorithm is to delete 3 connections in a network and connect them in another way, to find the most optimal results (Dorigo et al., 2006).

The parameter values influence the performance & convergence rate of the ACO algorithm. The optimal parameters of ACO are often different for each problem; there is no general value of a parameter that can be used to solve different problems. The mathematical formulation of the ACO algorithm is shown in the Equations below:

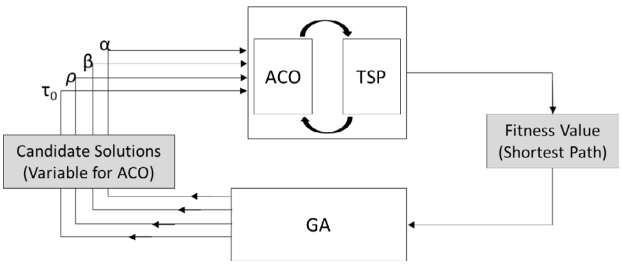
$$p_{ij}^k(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij_k}(t)\right]^{\beta}}{\sum_{s \subset allowed_k}\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij_k}(t)\right]^{\beta}}; \\ 0 \end{cases} \tag{1}$$

$$\tau_{ij}(t+1) = (1-\rho)\,\tau_{ij}(t) + \Delta\tau_{ij}(t); \tag{2}$$

$$\Delta\tau_{ij} = \begin{cases} \dfrac{Q}{L_k}, \\ 0 \end{cases} \tag{3}$$

with: p_{ij}^k – probability of ant k choosing path from node i to node j; τ_{ij} – pheromone concentration at path ij; η_{ij_k} – heuristic function of path ij for ant k (1/distance from i to j); α – importance of pheromone; β – importance of heuristic value; $\Delta\tau_{ij}$ – the change of pheromone concentration in path ij; ρ – pheromone evaporation coefficient; Q – pheromones coefficient; L_k – the total of distance for ant k in one tour; $Allowed_k$ = set of cities that has not been visited by ant k.

Referring to the mathematical equation used in ACO, four (4) parameters are used as control variables (the values of which are optimized using GA). These parameters were chosen because they have a very large influence on the final value produced. These four parameters are:
- α, pheromone weight;
- β, heuristic value weight;



Note: ACO is used to solve the TSP problem. The fitness value of the shortest route is then optimized using GA, resulting in candidate solutions for four parameters that are used to repeat the iteration process of finding the shortest route in the TSP problem.

Figure 2. The relationship between ACO and GA in completing TSP on the strategy being developed

- ρ, pheromone evaporation coefficient;
- τ_0, initial pheromone concentration.

In the developed strategy, the solution produced by ACO functions as a fitness function for GA, which creates new candidate solutions for ACO in each generation. The relationship between GA and ACO can be seen in Figure 2.

In solving TSP, not only by carrying out pure ACO mathematical operations but also by adding the drone capacity factor (C) to carry pesticides and the need for pesticides (d) at each target point. As a case example in this experiment, the capacity of each drone is set to 1 litre; however, in practical applications, this capacity may vary depending on the capabilities of the drone used. The need for pesticides is based on the health level of the plant at that point, where healthy conditions require 0.05 litre, unwell conditions require 0.075 litre and unhealthy conditions require 0.1 litre. The required value is a case example; in practical applications, the pesticide requirement greatly depends on the type of crop and the pesticide concentration. A representation of pesticide needs can be seen in Figure 3.

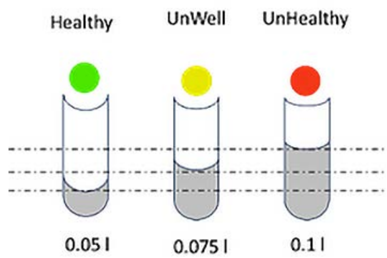


Figure 3. The dose of pesticide given at each level of plant health

The strategy developed consists of several interrelated algorithms. Figure 4 explains that there are several stages in this task allocation strategy, namely:
- GA Parameter Initialization
  1. Determine the values of several parameters, including the number of chromosomes, number of generations, Pc, Pm, and Er, as well as the range of values for the four optimized ACO parameters. This value range serves to limit the selection of permitted values. The four parameters have their range values (upper limit and lower limit) determined separately.
  2. The initial population contains 4 values which are the values of the four optimized ACO parameters. This value is generated randomly within a predetermined range.
- ACO Process Details
  3. In the ACO algorithm, determine the values of several parameters, including the number of ants, number of iterations, drone capacity, and depot (starting point). Apart from that, the distribution (matrix) of distances from the dataset used and the distribution of heuristic functions for each path are also generated.

4. Create a distribution of initial pheromone values for each path.
5. The probability of each path is calculated. The points are visited by ants once per iteration. Before moving, check the remaining fluid first. By paying attention to the fluid requirements at the next point, if fluid > 0 then the next point is selected according to the Roulette Wheel, whereas if fluid = 0 then the next point is the depot. The probability of selecting a point is based on the distance between points, the remaining fluid carried by the ants, and the fluid requirements at each point. Mathematically, the concept of the relationship between drone capacity and the opportunity to choose the next route is below:

$$C < 0 \text{ then } p_{ij}^{k} = 0 . \tag{4}$$

6. After the routes have been created, continue by calculating the total distance (fitness value) of the routes that have been created. The optimal value is the route length with the lowest/smallest value. Equation (5) is the fitness function used in this research:

$$Fitness = \sqrt{\left(X_1 - X_2\right)^2 + \left(Y_1 - Y_2\right)^2} . \tag{5}$$

7. Update the pheromone on each path by paying attention to the evaporation coefficient value.
8. If the iteration has not ended, the process is repeated from the starting point until the liquid runs out. The ACO processing process is repeated up to a predetermined maximum iteration.

- Integration of ACO and GA

9. If all iterations have been carried out, the optimal route length is determined. In the database, apart from the route length value, there is also data on the combination of parameters that produce this value. The values of the four ACO parameters that produce the shortest route length are used as the fitness function in the GA process.
10. The individual selection process at GA is carried out using the Roulette Wheel method.
11. The crossover process uses the arithmetic crossover method. Mathematically, Equation (6) is used to calculate the 1st child, while Equation (7) is used to calculate the 2nd child.

$$child\left[1\right] = r \times parent\left[1\right] + \left(1-r\right) \times parent\left[2\right]; \tag{6}$$

$$child\left[2\right] = r \times parent\left[2\right] + \left(1-r\right) \times parent\left[1\right]. \tag{7}$$

12. The GA process loop stops when it reaches its maximum generation. This method was chosen because the optimal route length value can change after reaching convergence in many repetitions without knowing the number of repetitions.
13. If several route length values and a combination of 4 parameter values have been obtained for each GA generation, then we search for the shortest route length for all GA generations. This value is used as the final value.

- 3Opt Application

14. The final results of processing using ACO and GA are then optimized using the 3Opt algorithm. This algorithm performs local optimization by reconnecting 3 routes to obtain more optimal results.

After the concept of the strategy being developed has been designed, an analysis is then carried out to find out whether the resulting multiple drones flight route pattern tends to form a particular pattern or spreads evenly to all points. In the strategy developed, several analyses were carried out on several parameters used. The analysis is carried out by focusing on the length of the resulting

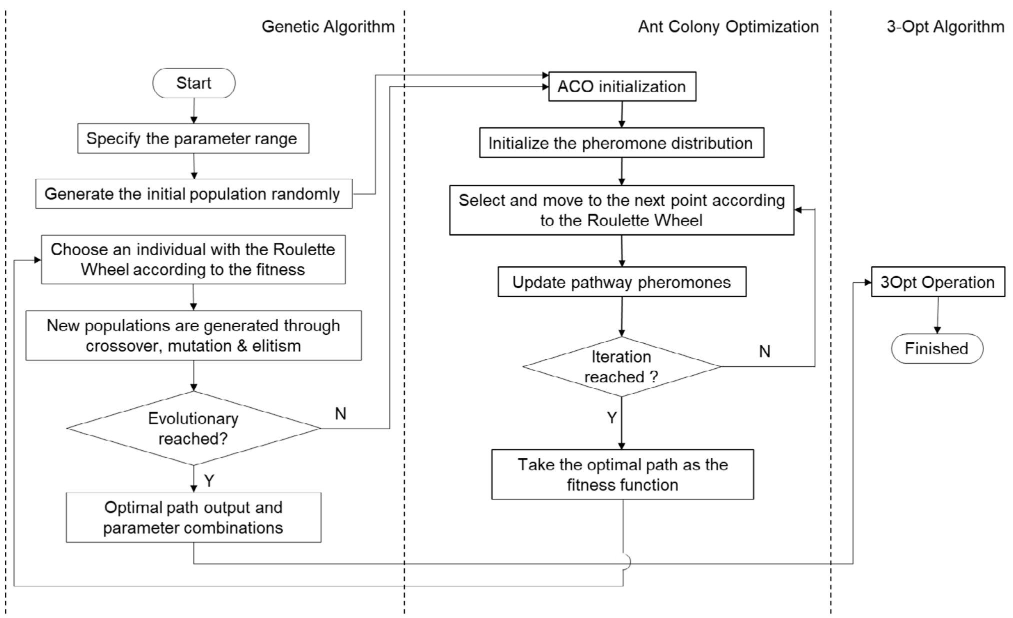


Figure 4. Flowchart of the developed route planning strategy

route and the computing time required. The algorithm parameters tested include:

- Number of generations of the GA algorithm;
- Upper & lower limits of optimized parameter values;
- Drone capacity;
- Number of chromosomes.

Apart from the parameters above, testing was also carried out by comparing the resulting route length when using the ACO+GA algorithm alone and when adding the 3Opt algorithm. The length of the resulting drone flight route has a higher priority than the required computing time; this is because the route length is a variable that has a real influence on its implementation (in this case, the spraying mission), while the computing time can be referred to as a process carried out at the ground station. And requires less effort.

3. Results and discussion

3.1. Spray drone target point dataset

The dataset used is the result of multispectral image processing from drone mapping. The resulting drone image consists of Red, Green, Blue, Near Infrared (NIR), and Red Edge (RE) bands. From this image, the level of plant health is processed using the Normalized Difference Vegetation Index (NDVI) approach, which uses the NIR and RE bands in its calculations. A classification process was carried out using the Random Forest algorithm to obtain results with reasonable accuracy. From this process, an accuracy of 96% was obtained, which means that the health level resulting from the NDVI process is in excellent agreement when compared with visual data in the field. Plant health levels are divided into three types: healthy, less-healthy & unhealthy.

From the image processing results above, a majority filter process is then carried out, which aims to generalize a reference pixel to match specified pixel area. Several factors influence this process, including the flying height of the spraying drone and the ability of the nozzle to carry out spraying (Wardana et al., 2023). Referring to the experience that has been carried out, the image pixel size is determined to be 2 x 2 meters, where this value is the same as the distance between points in the dataset.

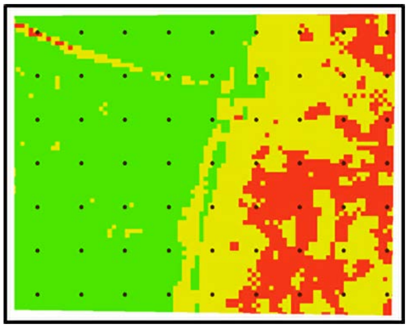


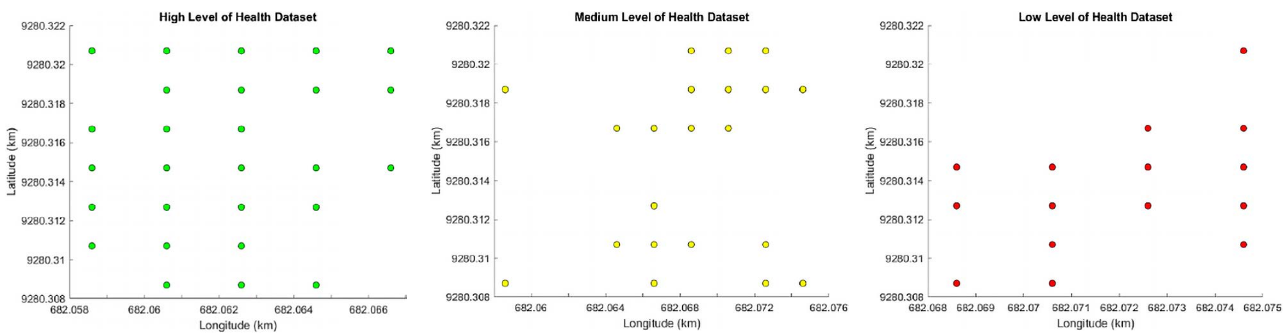
Figure 5. Representation of target points in the land object area

A total of 63 target points were used in this research. As shown in Figure 5, the points are spread equally with the distance between the points (X-axis and Y-axis) being 2 meters. Figure 5 is an overlay of target points on NDVI data. This research uses 2 dataset scenarios: a scenario with one health level category and a scenario with a combination of health levels. Differences in the number of categories in one dataset area result in differences in the amount of pesticide required at each point. The number of target points in each dataset is in Table 1. The healthy category is called a high level of health, less healthy is called a medium level of health, and unhealthy is called a low level of health.

Table 1. Type of dataset used and number of points

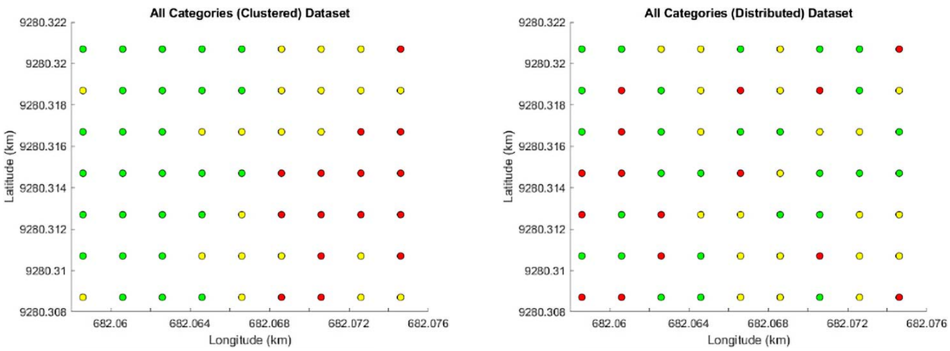
Datasets	Category Variations	Number of points
1	All categories are low	15
2	All categories are medium	21
3	All categories are high	27
4	All categories (high, medium, and low) – clustered	63
5	All categories (high, medium, and low) – distributed randomly	63

In a single health level category, the locations of the points tend to cluster in one area. It is necessary to analyze if the dataset points with a combination of health levels are in randomly distributed locations. The distribution of points with one health level category are in Figure 6, while points with a combination of health levels are in Figure 7.



a) b) c)

Figure 6. Point dataset with one health level category: (a) – high (healthy), (b) – medium (less healthy), (c) – low (unhealthy)



a) b)

Figure 7. Point dataset with a combination of health levels: (a) – all categories (clustered), (b) – all categories (distributed)

3.2. Testing the pattern of the developed strategy

Before conducting a more in-depth analysis of performance and results, the strategy developed is tested to determine its characteristics. The tendency to form a distribution pattern of multiple drones flight routes is the characteristic being tested. Testing was carried out using a homogeneous drone (same liquid capacity, namely 1 litre), a dataset with the same health category at all points (requiring the same pesticide dose, namely 0.1 litre/point) and each point was only visited once. The dataset used must have the same health category, because if they are different then there are varying pesticide needs at each point, resulting in the choice of the next point to be visited being influenced by pesticide needs. The position of the spraying drone depot is varied into 4 locations as in Figure 8.

From the four tests that were carried out using the adjusted dataset, the results obtained were that there were no tests that showed the formation of a particular flight route pattern. The resulting multiple drones flight pattern tends to spread evenly throughout the area (not concentrated at one point), taking into account the distance between target points and the health level of plants at the target point. The number of drones used depends on the number of routes formed. In all the depot variations above, all of them result in 4 routes being formed, where one route is indicated by a line from the depot and back to the depot. In one route there are no more than 10 points visited, this is because the drone capacity is 10 litres and the requirement is 0.1 litres/point.

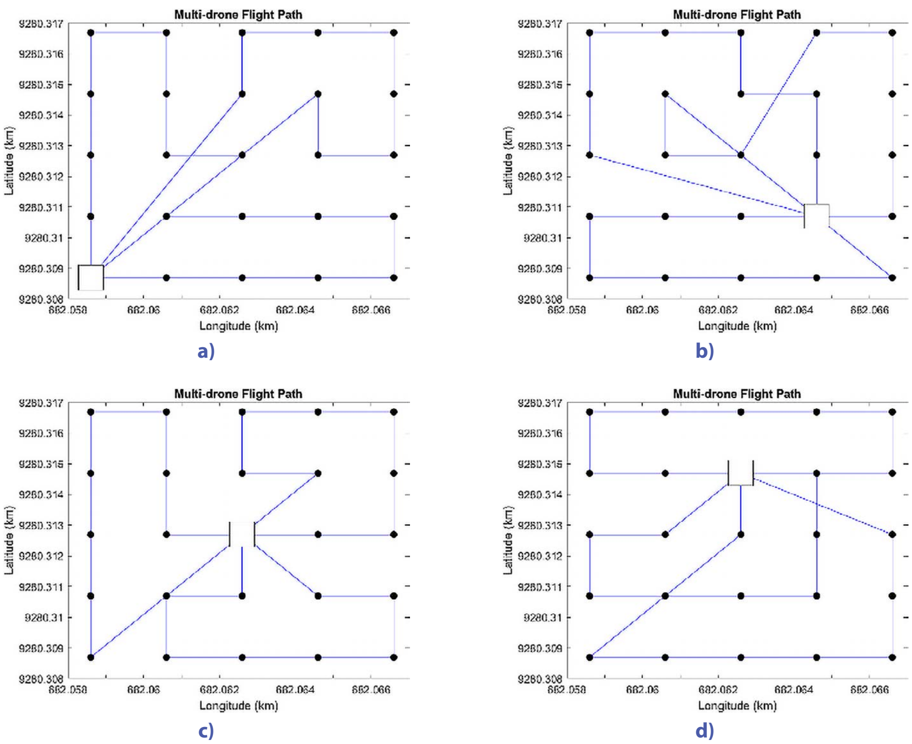


Figure 8. Pattern test results at several depot locations: (a) – Depot 13, (b) – Depot 1, (c) – Depot 18, (d) – Depot 9

3.3. Algorithm parameters testing

This test was carried out to determine the effect of the value of a parameter on the length of the resulting route and the required computing time. Several parameters are used in ACO and GA, but not all were tested in this study. The default values for these parameters are in Table 2 and Table 3. The value of a parameter changes when testing that parameter and becomes the default when testing other parameters. Testing was carried out on 5 types of datasets, the same for each type of test.

Table 2. Default values of ACO parameters

Drone capacity	Number of ants	Maximum iterations	Upper limit	Lower limit
1	10	10	15	0

Table 3. Default values of GA parameters

Probabilities of crossover	Probabilities of mutation	Elitism rate	Maximum generations	Genes	Number of chromosomes
0.95	0.05	0.2	100	4	4

This test is aimed at finding out whether the optimal route length produced gets smaller as generations increase. The test was not carried out to know the convergence of the processing, because there are random number factors which result in the convergence being at an unknown number of generations. Figure 9 shows the test results on the same dataset with repetition 6 times. Testing was carried out by determining 1000 generations. It can be seen that there are no similarities or similarities in the occurrence of convergence. The optimal route length value is also different for each iteration. Both of these things are due to the presence of random values in the processing carried out.

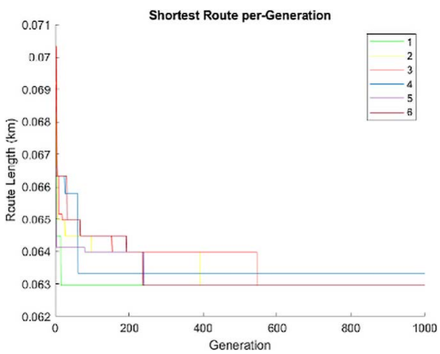
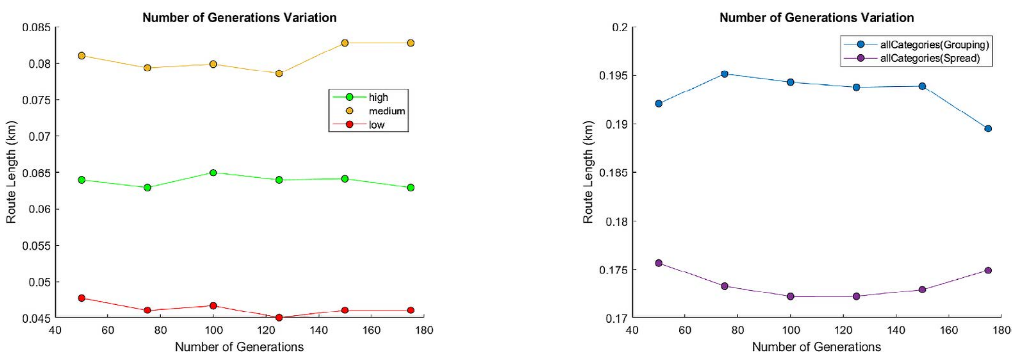


Figure 9. Test results on the same dataset with repetition 6 times

First, we tested the influence of the number of generations of the GA algorithm. The number of generations varied at several values, namely 50, 75, 100, 125, 150, and 175. In Figure 10, all scenarios show that the number of generations does not significantly affect the resulting optimal route length, because the number of generations plays a role in providing additional value combination options. However, increasing the number of generations provides more opportunities for solution exploration, which can improve the robustness of the search process even if it does not always yield shorter routes. This finding indicates that, beyond a certain point, the search space may already be sufficiently explored, and additional generations contribute more to computational cost than to solution improvement. Therefore, there is a trade-off between computational efficiency and exploration depth.

In Figure 11, all scenarios show that all datasets have something in common: the greater the number of generations, the more computing time increases. This is because the number of combinations of parameter values tested increases with the increasing number of generations. In Figure 11a it can be seen that the difference in the number of points in the dataset al.o affects the computing time required, where the greater the number of points, the greater the computing time. This is because the greater the number of points, the more points must be visited, so the route search process takes longer. This rule applies in Figure 11b, where if the number of points is the same then the computing time tends to be the same regardless of the presence of the points. This is because the time required to calculate the distance is the same wherever the points are located.



a) b)

Figure 10. Test results of the effect of varying the number of GA algorithm generations on route length: (a) – Scenario 1, (b) – Scenario 2

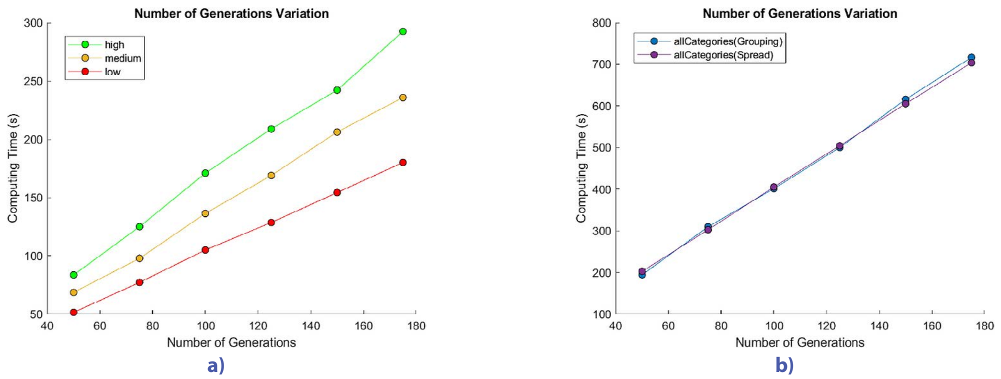


Figure 11. Test results of the effect of varying the number of generations of the GA algorithm on computing time: (a) – Scenario 1, (b) – Scenario 2

Second, tests were carried out on the value ranges of several optimized ACO parameters. There are two parameter value limit tests: upper limit and lower limit. Variations in the upper and lower limit values are used to limit the values of α, β, and τ_0 only, while the limit value of ρ is set in the range 0–1. The upper limit test is carried out by setting the lower limit value at 0 in all test variations, while the variations in the upper limit value are in Table 4. The lower limit test is carried out by setting the upper limit value at 15 in all test variations, while the variations in the lower limit value are in Table 5.

Table 4. The upper limit variations of parameter values (fixed lower limit value)

Parameter	Test					
	1	2	3	4	5	6
Upper limit	2.5	5	7.5	10	12.5	15
Lower limit	0	0	0	0	0	0

Table 5. The lower limit variations of parameter values (fixed upper limit value)

Parameter	Test					
	1	2	3	4	5	6
Upper limit	15	15	15	15	15	15
Lower limit	0	2.5	5	7.5	10	12.5

It can be seen in Figure 12 and Figure 13 that the upper limit and lower limit values do not affect the resulting route length in both scenarios, because the limit value only limits the range of values of the four ACO parameters that are allowed but does not guarantee that the combination of given parameter values can produce the optimal route length. This finding suggests that the algorithm's performance is relatively robust to parameter range variations. The limited sensitivity indicates that the algorithm effectively searches within the feasible space, and that most of the parameter combinations already produce near-optimal solutions. From an optimization perspective, this implies that the problem's search space may not be highly dependent on extreme parameter values, and therefore the tuning process can prioritize computational efficiency over exhaustive parameter exploration. In practical terms, this stability is beneficial because it reduces the need for extensive manual tuning, allowing for faster adaptation of the algorithm to different datasets with minimal loss of performance.

In Figure 14 and Figure 15, it can be seen that the limit value does not affect the required computing time. This is because the limit value only limits the range of values of the four ACO parameters allowed, so the number of combinations of parameter values tested remains the same and not depend on the range of values.

From all tests related to this value range limit, the results were also obtained that the optimal parameter values

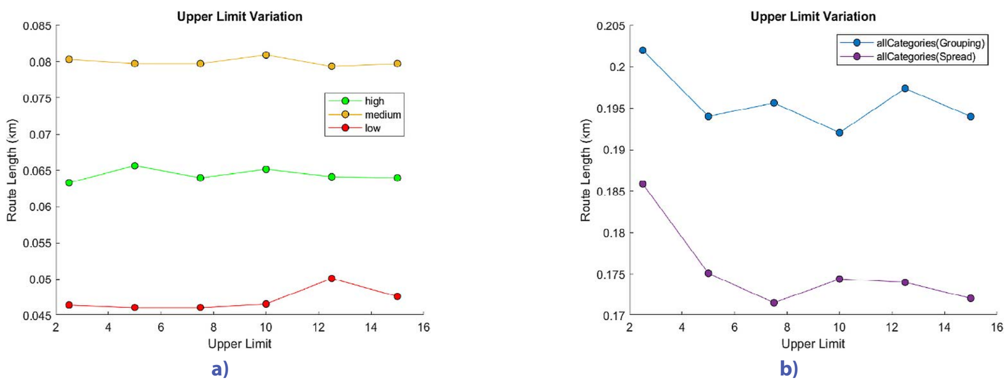


Figure 12. Test results of the influence of variations in the upper limit of parameter values on route length: (a) – Scenario 1, (b) – Scenario 2

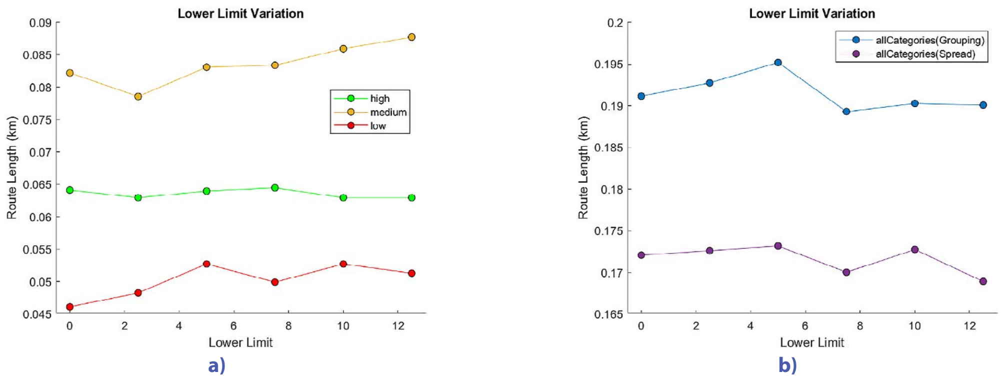


Figure 13. Test results of the effect of variations in the lower limit of parameter values on route length: (a) – Scenario 1, (b) – Scenario 2

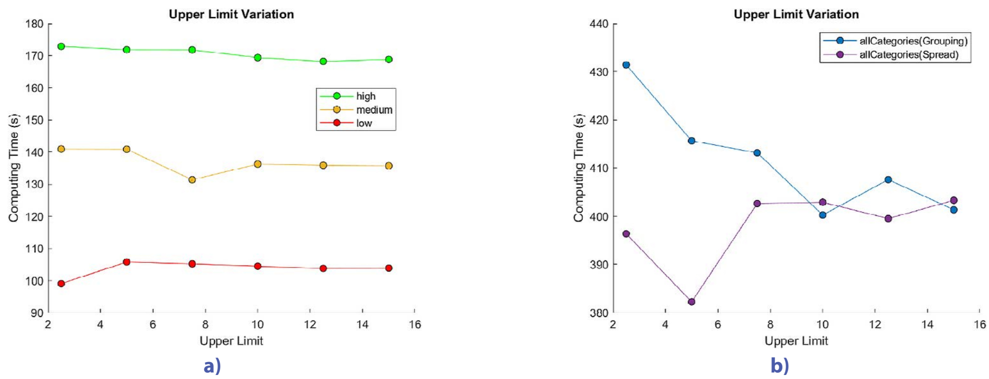


Figure 14. Test results of the influence of variations in the upper limit of parameter values on computing time, (a) – Scenario 1, (b) – Scenario 2

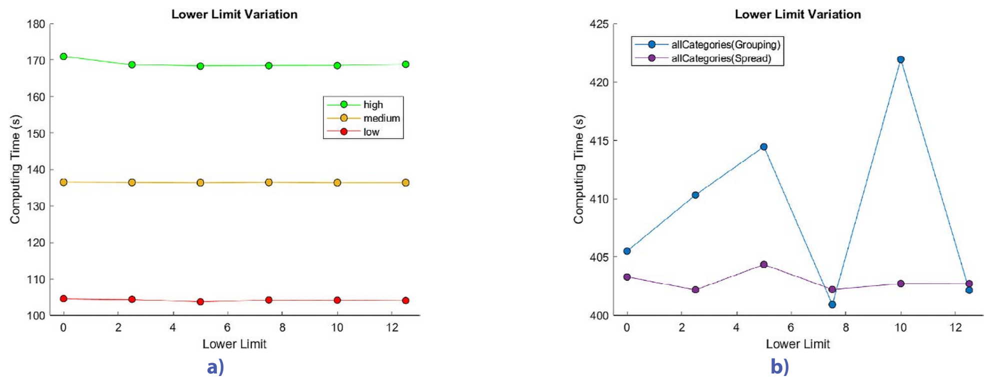


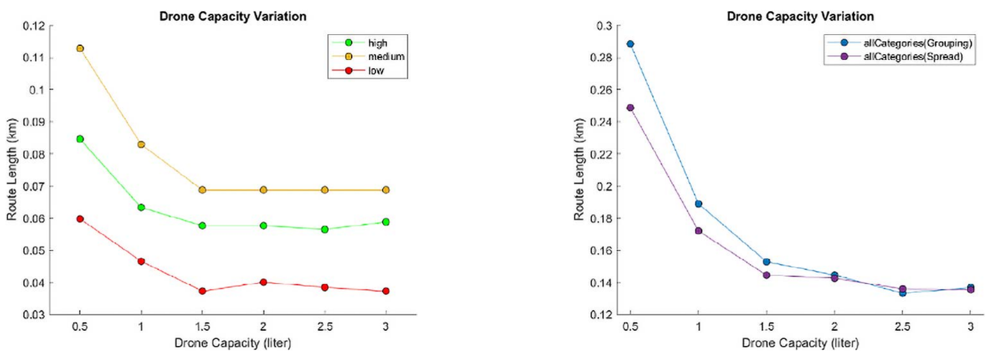
Figure 15. Test results of the effect of variations in the lower limit of parameter values on computing time: (a) – Scenario 1, (b) – Scenario 2

were within the predetermined range, and the selected parameter values would not be outside the predetermined range. Table 6 shows the values of the four parameters optimized using GA by providing variations in the value range, where the upper and lower limits are determined. From this table, it is also known that the standard deviation value of the resulting route length is 0.000817, which means that all optimal routes have a substantial level of similarity. It shows that the strategy implemented has tried to find the optimal value of the existing problems.

Third, testing was carried out on the influence of drone capacity parameters. The capacity in question is the amount or volume of liquid the spraying drone carries during the spraying mission. In this test, the drone capacity was varied at several values, namely 0.5, 1, 1.5, 2, 2.5, and 3 liters. Figure 16 shows the test result of varying the drone capacity. It can be seen that the length of the drone flight route has decreased significantly along with the increase in drone capacity of up to 1.5 liters, which is almost the same for several capacities after that. This is because the drone's with very small capacity results in the drone often returning to the depot (starting point) to refill fluids. Calculating the route, length also includes the distance between the depot and the first point and between

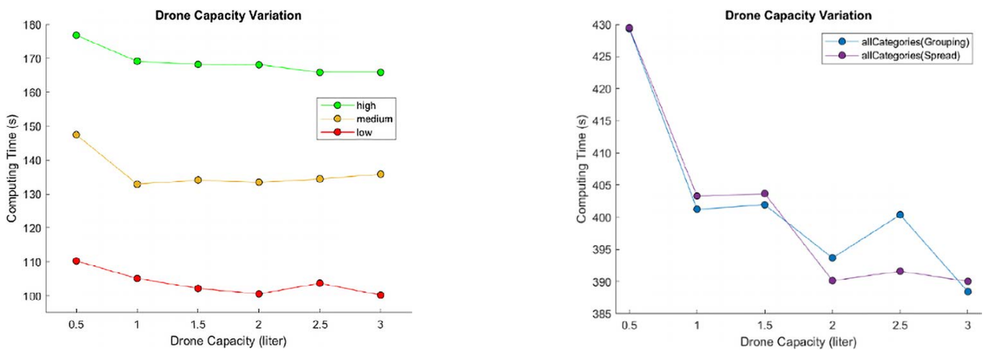
Table 6. Optimized values of the four parameters with variations in the upper and lower limits

Lower limit	Upper limit	τ_0	ρ	α	β	P
0	2.5	0.36870369	0.313819971	1.440121817	2.142662923	0.17961
0	5	3.040266516	0.325078425	2.321777941	3.971156124	0.17196
0	7.5	1.240659437	0.437093518	2.689767562	3.824083364	0.1743
0	10	7.970141034	0.955600333	1.709938365	6.856770226	0.17068
0	12.5	6.424538014	0.763116957	1.806466078	10.33628833	0.17024
0	15	11.18175915	0.18688572	10.40893785	9.770689417	0.17267
0	15	9.230502567	0.635461959	3.316818196	14.68773977	0.17238
2.5	15	9.853279301	0.454054595	3.107615924	13.37161479	0.17019
5	15	10.26715285	0.651117728	8.885343841	9.156234232	0.17301
7.5	15	10.2828367	0.387444233	12.42935663	9.650476237	0.17507
10	15	14.18232023	0.176870092	12.04693873	10.09250858	0.17051
12.5	15	13.12817475	0.381538866	14.9759603	13.72481318	0.17677
Average						0.17312
Max						0.17961
Min						0.17019
Standard Deviation						0.000817



a) b)

Figure 16. Test results of the effect of varying drone capacity on route length: (a) – Scenario 1, (b) – Scenario 2



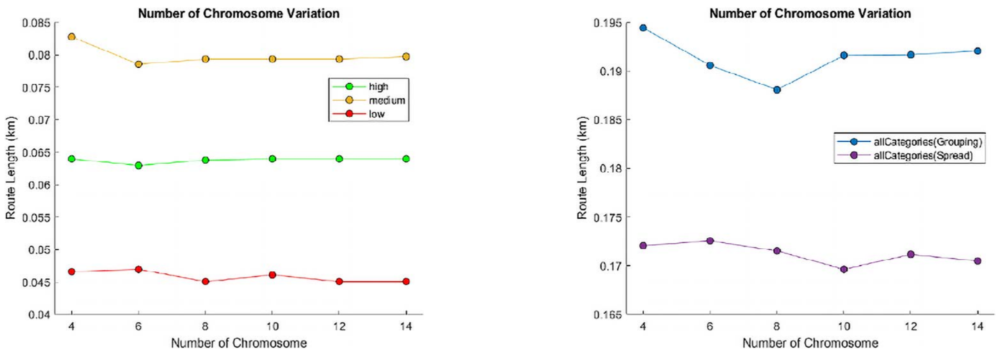
a) b)

Figure 17. Test results of the effect of varying drone capacity on computing time: (a) – Scenario 1, (b) – Scenario 2

the last and the depot. Therefore, the route also increases as the drone returns to the depot more often.

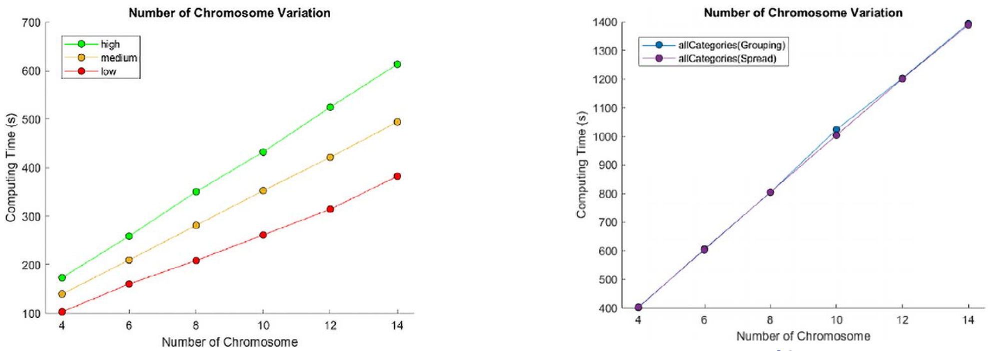
Computing time tends to decrease as drone capacity increases, as in Figure 17. This is because the greater the drone capacity, the program iterations resulting from the drone's frequent return to the depot can be reduced.

Fourth, the influence of chromosome number were tested. The test was carried out by varying the number of chromosomes to several values, namely 4, 6, 8, 10, 12, and 14. Figure 18 shows the effect of the number of chromosomes on the route length. In both scenarios, the number of chromosomes does not significantly influence



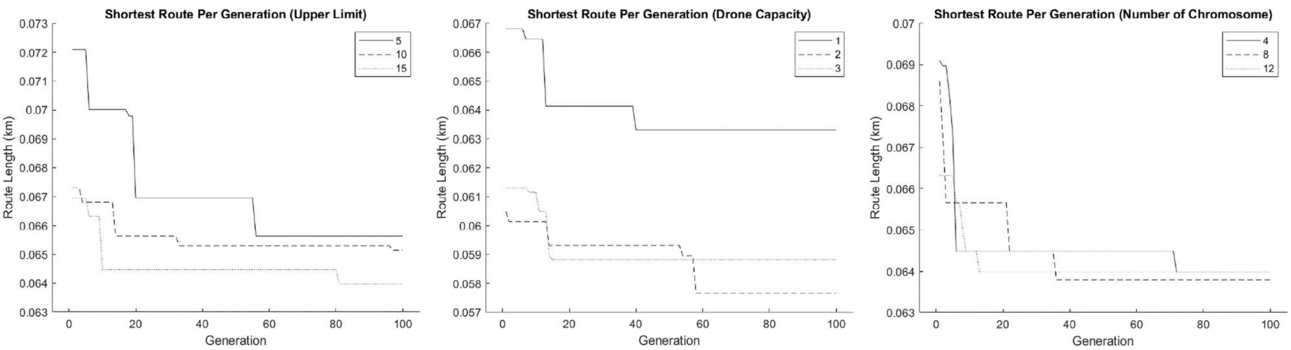
a) b)

Figure 18. Test results of the effect of variations in chromosome number on route length: (a) – Scenario 1, (b) – Scenario 2



a) b)

Figure 19. Test results of the effect of variations in chromosome number on computing time: (a) – Scenario 1, (b) – Scenario 2



a) b) c)

Figure 20. The effect of GA on the shortest route for each generation in several parameter variations: (a) – lower limit parameters, (b) – drone capacity parameters, (c) – chromosome number parameters

the length of the resulting route, because the number of chromosomes does not influence the determination of the optimal test parameter values.

Figure 19, shows that the number of chromosomes greatly influences the computing time required, where the greater the number of chromosomes, the greater the time required for data processing. This is because the more chromosomes there are, the more combinations of parameter values are tested.

From all test results related to route length (Figures 10, 12, 13, 16, and 18) in scenario 1 (All Figures (a)), it can be seen that the route length of the less healthy category is generally greater than the healthy category even though the number of points is less, this is because the location of points in the less healthy category tends to be spread out, several points are located very far from the location of points in general. On the other hand, in the healthy category, dots tend to gather in close locations. The unhealthy category has the smallest route length because the number of points is the smallest and are located close to each other. Meanwhile, scenario 2 (All Figures (b)) shows that having the same number of points does not guarantee that the length of the resulting route is also the same. This is because the dataset used has three health level categories whose distribution of points differs. The length of the route is not only determined based on the distance between points but is also determined based on the need for pesticides at each point and the drone's capacity to carry pesticide.

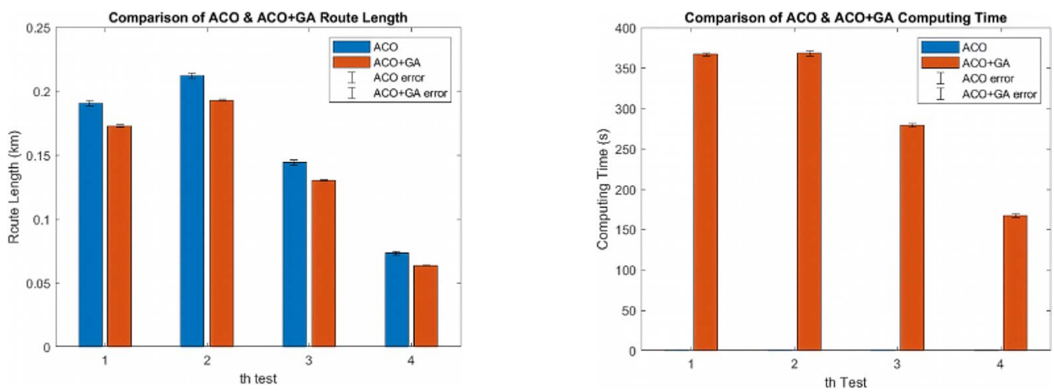
Analysis was also carried out on several ACO and GA parameters. The results showed that increasing generations of the GA algorithm would result in the drone flight route length being the same or getting smaller. For example, in Figure 20a, where the upper limit variation test was carried out, Figure 20b carried out drone capacity testing, and Figure 20c tested the number of chromosomes. All these tests were done in the same dataset category and the number of generations was determined to be 100. All the variations in parameter values show that the optimal route length produced in the first generation is longer than in the 100th generation. Some values get smaller in the second generation but are also found in subsequent generations. This shows that the process of selecting the combination of the four ACO parameters is running optimally.

3.4. Implementation of the genetic algorithm

Tests were conducted to compare the resulting route length and the computing time required if the ACO algorithm was used alone and if GA was added. Both test scenarios were carried out with the same ACO parameter values: the number of ants was 10, the ACO iteration was 100, and the drone capacity was 1 litre. Testing was carried out on 4 different datasets: all categories (clustered), all categories (spread), healthy-unhealthy categories and healthy categories.

The ACO algorithm is tested by manually providing parameter values which are determined randomly. Meanwhile, ACO+GA testing is carried out by providing parameter values automatically according to the strategy developed.

Optimal ACO results depend on the parameter values, which can differ from one problem to another. In several studies, this value was directly determined manually (Ahuja & Pahwa, 2005; Gite et al., 2023; Xu et al., 2023; Tamura et al., 2021; Zouein & Kattan, 2022), even though it is not guaranteed to produce optimal values. The use of GA to optimize ACO parameters has a positive impact; namely, the process of finding optimal ACO parameters is carried out more quickly because it is done automatically by GA. From the testing, in Figure 21(a) it was found that the route length produced by the ACO+GA algorithm was shorter than using ACO alone with an efficiency of 10%. This more efficient result is because the values of the four parameters optimized with GA have values with a level of accuracy up to 5 digits after decimal point, while the parameter values with ACO alone are random integers. The results obtained in this study are superior to previous similar research, where a Modified Ant Colony Optimization (MACO) combined with Genetic Algorithm (GA) was applied for autonomous vehicle path planning (Heng & Rahiman, 2025). In that research, the approach – known as the Modified Ant Colony Optimization and Genetic Algorithm (MACOGA) – was designed for grid-based environments and integrated a probabilistic prediction mechanism to enhance node selection by combining heuristic and probabilistic factors. This hybrid method improved both path length and computation time, with the shortest route achieving an efficiency improvement of up to 6%. Compared to MACOGA, the ACO+GA model developed in this study produced a higher route optimization efficiency of 10%, demonstrating better performance in minimizing path length, although it required longer computational time due to the extensive parameter optimization process. In Figure 21b it can be seen that the computing time required for ACO+GA takes 100% longer than using ACO alone. This is because to find the most optimal value in one processing, ACO+GA must carry out 10,000 repetitions, whereas ACO only has one repetition. However, from the tests that have been carried out it is found that GA convergence is in different generations. Convergence is not at 100% of the number of iterations, but is at around 30–50% of the number of iterations.



a) b)

Figure 21. Comparison of ACO and ACO+GA algorithms strategy: (a) – route length, (b) – computing time

3.5. Implementation of the 3Opt algorithm

The routes generated by the ACO+GA algorithm are then processed using the 3Opt algorithm. The 3Opt algorithm functions as a local optimization by swapping the three edges of the previous route. Testing was carried out on seven types of datasets with different numbers of drone target points. In Figure 22, it can be seen that the route length produced by the ACO+GA algorithm is more significant than when the 3Opt algorithm was added. Applying the 3Opt algorithm provides efficiency regarding route length, which is around 4%. The proposed hybrid ACO–GA–3Opt achieved a 13.6% shorter total flight route than standard ACO and a 10% improvement over ACO–GA. These quantitative improvements demonstrate the effectiveness of combining global search (GA) with local refinement (3Opt). This more efficient result would be beneficial if it were implemented in practice in the field because fewer batteries would be used, and flight time would also be more efficient.

An example of the results of developing a multiple drones coordination strategy can be seen in Figure 23, where route planning is carried out from the spray drone target points so that several routes are produced, illustrated with different colors between routes. In future implementation, one drone will carry out each route simultaneously and each point will be visited once by one spray drone. In the case of Figure 23, 3 drones will be used to carry out pesticide spraying missions.

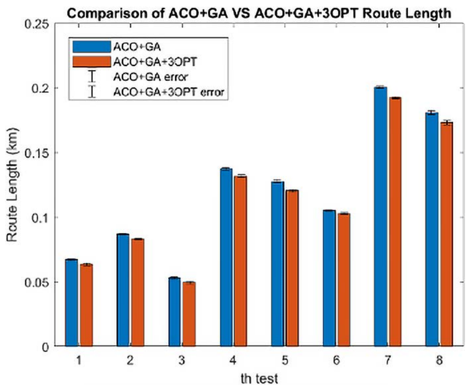


Figure 22. Comparison of route lengths generated by the ACO+GA and ACO+GA+3Opt algorithms

4. Conclusions

This study presents an intelligent agricultural management strategy designed to improve crop yields while minimizing the environmental impact of excessive pesticide use. The proposed approach enhances time efficiency in field operations and reduces the workload of rice field cultivators by employing multiple-drones for precision spraying. The strategy focuses on optimizing multiple-drone flight routes based on plant health levels using a combination of Ant Colony Optimization (ACO), Genetic Algorithm (GA), and 3-Opt local search. Since the performance of ACO depends heavily on parameter settings that vary across problems, GA is used to automatically tune these parameters, significantly accelerating the optimization process compared to manual tuning. The integration of 3-Opt further improves route efficiency through local optimization, resulting in shorter total flight distances. Experimental results indicate that the combination of GA, ACO, and 3-Opt enhances route planning efficiency by up to 13.6% compared with conventional ACO. Route length is a critical factor in real spraying missions, as it directly influences drone battery consumption and overall mission completion time. Combined GA-ACO-3Opt can reduces flight distance, expedites mission time, and mitigates environmental impact. The proposed framework demonstrates strong potential for improving the sustainability and effectiveness of drone-based pesticide spraying in precision agriculture.

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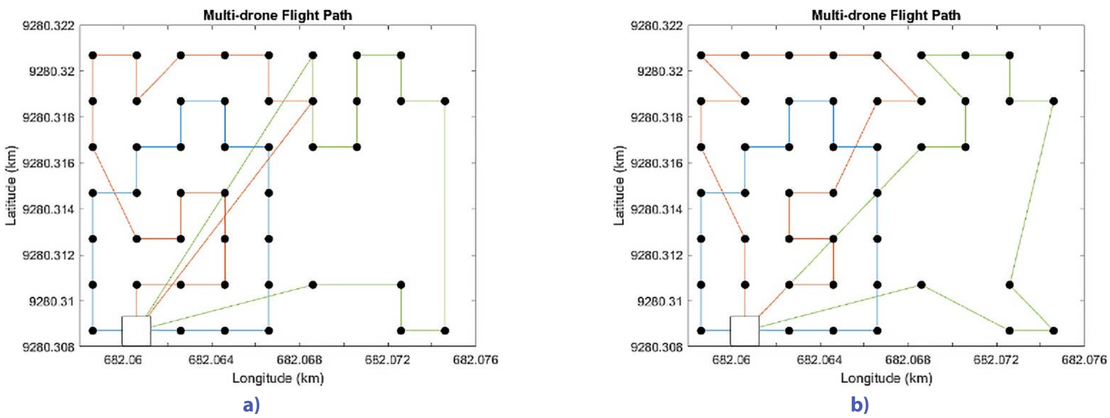

Figure 23. Examples of coordinated multiple drones flight routes: (a) – before 3Opt, (b) – after 3Opt

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