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Comparative Analysis of Genetic and Greedy Algorithm for Optimal Drone Flight Route Planning in Agriculture

Tarımda Optimal Drone Uçuş Rotası Planlaması için Genetik ve Açgözlü Algoritmanın Karşılaştırmalı Analizi

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COMPARATIVE ANALYSIS OF GENETIC AND GREEDY ALGORITHM FOR OPTIMAL DRONE FLIGHT ROUTE PLANNING IN AGRICULTURE

ABSTRACT

In this study, the performance of the Genetic Algorithm (GA) in optimizing the agricultural drone flight route was compared with the Greedy Algorithm, revealing that GA produce routes that are, on average, 17.44 % more efficient. This efficiency, measured over 500 generations in a static field model, suggests substantial potential for saving resources and time in agricultural operations. Despite the effectiveness of the GA, its computational intensity limits real-time field applications, but offers advantages in offline route planning for pre-mapped areas. A t-test between flight lengths which are created by the algorithms highlighted a significant difference, with a p-value of approximately 7.18×10^{-9}, indicating the GA's superior performance. Future research should aim to bridge the gap between the simplified binary field model used in simulations and the complexities of real-world agricultural landscapes to improve the practical deployment of GAs in drone route optimization.

Keywords: Agricultural Drone, Drone Route Optimization, Offline Route Planning.

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TARIMDA OPTİMAL DRONE UÇUŞ ROTASI PLANLAMASI İÇİN GENETİK VE AÇGÖZLÜ ALGORİTMANIN KARŞILAŞTIRMALI ANALİZİ

ÖZ

Bu çalışmada Genetik Algoritmanın (GA) tarımsal dronların uçuş rotasını optimize etmedeki performansı Açgözlü Algoritma ile karşılaştırılmıştır. GA'nın ortalama %17,44 daha kısa rotalar ürettiği görülmüştür. Statik olarak simüle edilen bir saha modelinde, genetik algoritmada 500 nesil üzerinden ölçülen bu verimlilik, tarımsal faaliyetlerde kaynak ve zaman tasarrufu açısından önemli bir potansiyele işaret etmektedir. GA'nın etkinliğine rağmen hesaplama yoğunluğu, gerçek zamanlı saha uygulamalarını sınırlandırmaktadır, ancak önceden uygulama haritası hazırlanmış alanlar için çevrimdışı rota planlamada avantajlar sunmaktadır. Algoritmaların rastgele olarak üretilen uçuş simülasyonlarında üretmiş oldukları rota uzunlukları arasında t-testi kullanılarak yapılan karşılaştırmada GA tarafından üretilen rotaların istatistiksel olarak anlamlı seviyede kısa olduğu görülmüştür ($p=7.18\times10^{-9}$). Gelecekteki araştırmalarda, GA'ların dron rota optimizasyonun-

da pratik kullanımını geliştirmek için simülasyonda kullanılan basitleştirilmiş model ile gerçek dünya uygulamalarındaki karmaşıklık arasında bulunan farkları gidermek amaçlanacaktır.

Anahtar Kelimeler: Dron Rota Optimizasyonu, Çevrimdışı Rota Planlama, Tarımsal Dron.

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1. INTRODUCTION

For agricultural purposes, optimizing the shortest flight route for drone flight is essential because it directly influences the efficiency and effectiveness of crop management and monitoring. Precision agriculture relies on drones to perform tasks such as spraying pesticides, fertilizing, seeding, and surveying crops (Banpurkar et al., 2021; Chen et al., 2021; Marzuki et al., 2021; Rachmawati et al., 2021; Hafeez, et al., 2022). By ensuring the shortest and most efficient routes, drones can cover more acreage with less battery usage and time, reducing operational costs and environmental impacts (Agrawal et al., 2021; Vazquez-Carmona et al., 2022). This optimization leads to more targeted application of agricultural inputs, minimizing waste, and maximizing crop yields. Essentially, the shortest flight route maximizes the benefits of drone technology in precision agriculture, leading to smarter and more sustainable farming practices (Srivastava et al., 2020).

Currently, various algorithms and technologies are employed to determine the optimal flight routes for tasks such as drone flight in agriculture. These include classical approaches such as Dijkstra's and A* for static environments and more sophisticated methods such as genetic algorithms, ant colony optimization, and particle swarm optimization, which can handle dynamic and complex scenarios (Abdulsaheb and Kadhim, 2023; Sundarraj et al., 2023; Wu et al., 2023). Machine learning models, particularly reinforcement learning, are increasingly used to adapt to changing conditions and to learn from the environment (Qu et al., 2020; Yan et al., 2020). Additionally, real-time data processing with geographic information system (GIS) and global positioning system (GPS) integration allows for the adjustment of flight paths based on immediate environmental feedback, such as weather changes or crop growth patterns (Manfreda and Eyal, 2023). These methods are complemented by advances in sensor technology and data analytics, enabling more precise mapping and monitoring, which in turn leads to more efficient flight-route planning and resource use (Pepe et al., 2018; Yu and Zhang, 2015).

Genetic algorithms (GAs) offer a robust and flexible approach for searching for optimal routes, particularly in complex and multi-dimensional spaces where traditional algorithms might falter (Li et al., 2020; Zhai and Feng, 2022; Zou et al., 2023). Their evolutionary nature allows them to explore a vast search space and avoid being trapped in local optima, making them highly effective for problems such as route optimization, where the landscape of possible solutions is rugged and full of potential pitfalls. GAs can simultaneously evaluate many different routes, learning, and improving over successive generations, which enables them to converge on a highly efficient solution, even in the face of constraints and varying conditions. This adaptability, coupled with their ability to incorporate real-world variables and heuristics into their fitness functions, makes genetic algorithms a powerful tool for finding optimal routes in dynamic environments, such as drone navigation in agriculture, where terrain, obstacles, and areas of interest can change over time.

The purpose of this study is to create an algorithmic solution that can find an efficient flight route for spraying a field with certain areas that require treatment. The field was represented as a grid, with some cells needing spraying (black) and others not (white). The algorithmic solution aims to determine the shortest possible route that covers all areas that need spraying, which is analogous to the Traveling Salesman Problem (TSP) (Cheikhrouhou and Khoufi, 2021).

In this study, we used two algorithms to solve this optimization problem. The Genetic Algorithm (GA) uses evolutionary strategies to refine solutions across generations, aiming to minimize flight routes and find the most efficient route in terms of length. Conversely, the Greedy Algorithm selects the closest next point at each step to build a solution, ensuring that all required points are visited.

The program compares these two approaches by plotting the flight routes and calculating the total distance length of each route. This comparison can help to understand the strengths and weaknesses of each algorithm.

2. MATERIAL AND METHODS

2.1. Simulation Grid Design and Probabilistic Data Generation

The study area was a simulated grid that reflected the variability of an actual field. The study was conducted over a 10x10 grid for simplicity to represent an agricultural field. Every grid has 1m by 1m side lengths. Data on areas requiring spraying were generated using a random binary distribution with a 70 % probability for non-spray zones and 30 % probability for spray zones (Hussain et al., 2020; Leshkenov, 2023), simulating patches of crops requiring treatment.

2.2. Algorithm İmplementation

Two algorithms were implemented for route optimization: A Genetic Algorithm (GA) and a Greedy Algorithm. The GA was developed using Distributed Evolutionary Algorithms in Python (DEAP) library (Fortin et al., 2012), which facilitated the creation of a population of potential routes, the definition of a fitness function based on the total route length and a penalty for inefficient moves, and the application of evolutionary operators such as crossover, mutation, and selection. The Greedy Algorithm is custom-coded to iteratively select the nearest unvisited point. The GA's implementation through the DEAP library showcases the use of evolutionary concepts to optimize the route, whereas the Greedy Algorithm provides a baseline for comparison with GA.

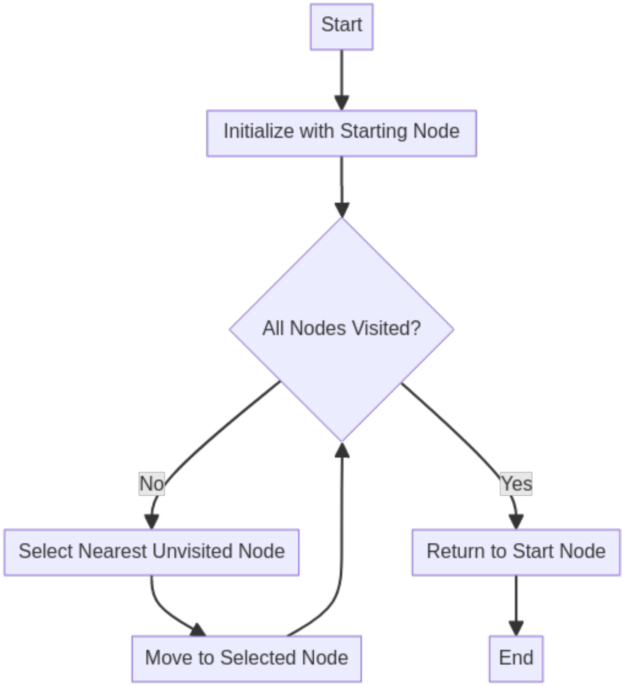


Figure 1. Greedy Algorithm

Figures 1 and 2 provide the visual workflows for the Greedy and Genetic algorithms, respectively, applied to route optimization. Figure 1 outlines a straightforward Greedy Algorithm that selects the nearest unvisited node until all nodes are covered, and returns to the start upon completion. In contrast, Figure 2 presents a Genetic process, which begins by initializing a population of solutions and iteratively evolves this population through a series of generations using genetic operations until the maximum number of generations is reached; subsequently, the best solution is selected.

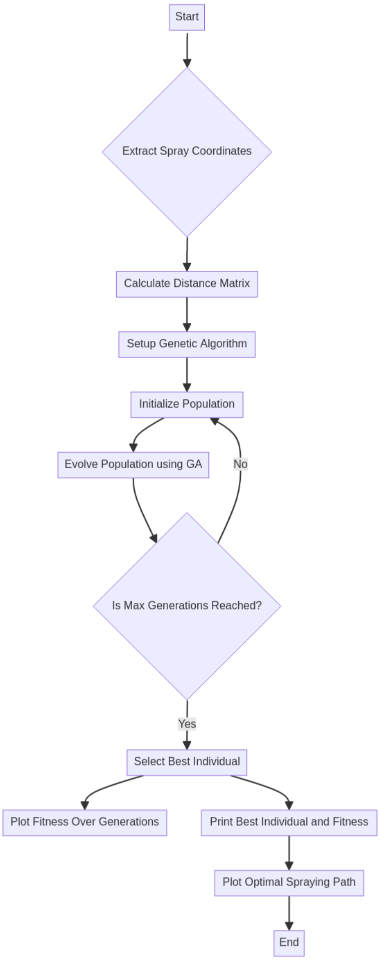


Figure 2. Genetic Algorithm

2.3. Route Optimization Process

For the GA, a population of 10000 routes was evolved over 500 generations with a crossover probability of 0.8 and a mutation probability of 0.1. The Greedy Algorithm starts at a fixed point and sequentially adds the nearest unvisited point to the route. Both algorithms aimed to minimize the total distance traveled while ensuring that all required points were visited. We conducted an objective evaluation of both methods, focusing on the total flight length, which is a critical factor for operational efficiency.

2.4. Evaluation Metrics

The performance of the algorithms was assessed based on the total flight length of the final route. The GA fitness over generations was plotted to visualize the optimization process. The route length difference between the greedy algorithm and the GA was calculated using the following formula:

$$Flight\ Route\ Length\ Difference(\%) = \left(\frac{V_g - V_{ge}}{V_{ge}}\right) x100 \qquad (1)$$

V_g: Flight route lenght of greedy algorithm

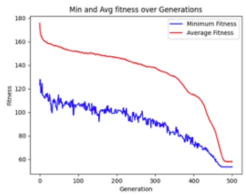
V_{ge}: Flight route length of genetic algorithm

2.5. Visualization

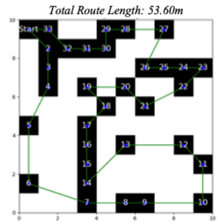
The routes generated by both algorithms were visualized using Matplotlib (Hunter, 2007) to compare their efficiency and coverage. The visualization includes the sequence of points visited and the total distance covered by each algorithm. Visualization plays a key role in interpreting the results, offering an intuitive understanding of the performance of each algorithm.

3. RESULTS AND DISCUSSIONS

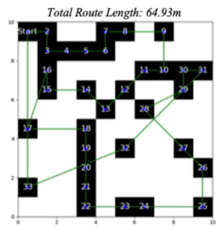
In the context of a Genetic Algorithm (GA) applied to optimize flight route planning, a population of 10000 possible routes was subjected to an evolutionary process spanning 500 generations. GA employs a fitness function designed to evaluate and minimize the total length of each flight route. Through iterative refinement across generations, the algorithm seeks to progressively reduce the cumulative travel length, thereby enhancing route efficiency. Figure 3-4(a) illustrates the progression of the fitness function over these generations, visually depicting the improvement in the route optimization. Subsequently, Figures 3-4(b) and 3-4(c) provide comparative visualizations of the flight routes as determined by the Genetic Algorithm and the greedy algorithm, respectively. These figures show the outcomes of both algorithms in terms of route efficiency, with the Genetic Algorithm typically outperforming the Greedy Algorithm by producing shorter and more efficient routes.



a) Fitness values over generations for genetic algorithm

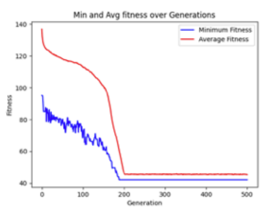


b) Flight route generated by genetic algorithm

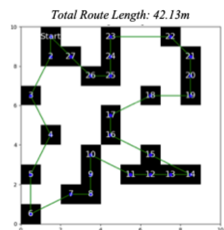


c) Flight route created by greedy algorithm

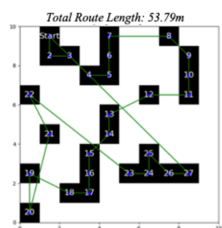
Figure 3. Sample flight route generated by genetic and greedy algorithms



a) Fitness values over generations for genetic algorithm



b) Flight route generated by genetic algorithm



c) Flight route created by greedy algorithm

Figure 4. Sample flight route generated by genetic and greedy algorithms

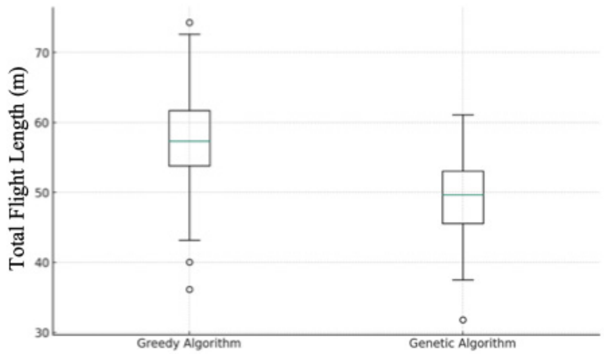


Figure 5. Comparison of total flight route length for greedy and genetic algorithms

The boxplot provides a visual comparison of the total flight route lengths calculated using greedy and genetic algorithms (Figure 5). The central line in each box represents the median of the data, which provides a sense of the central tendency for the flight length of each algorithm. The boxes themselves span from the first quartile (Q1) to the third quartile (Q3), representing the middle 50% of the data, providing insight into the distribution and spread. The "whiskers" extend from the boxes to show the range of the data, excluding outliers that are plotted as individual points beyond the whiskers. From this plot, we can discern that the Greedy Algorithm tends to have longer flights than the Genetic Algorithm, as indicated by the position of the median and the spread of the data. The outliers in each algorithm suggest the presence of cases in which the total flight length is significantly different from typical ranges. We believe that this was due to the stochastic nature of the random simulation environment in each trial.

Upon a deeper analysis of the boxplot data, we found that the Greedy Algorithm had a higher average total flight length at approximately 57.91 m compared to the Genetic Algorithm's average of approximately 49.37 m. This indicates that on average, the Greedy Algorithm tends to produce longer flight routes.

The median value was slightly lower than the average for the Greedy Algorithm at approximately 57.35 m, suggesting a slightly skewed distribution of data. In contrast, the median flight length for the Genetic Algorithm was almost equal to its average at approximately 49.65 m, which implies a more symmetric distribution of data points around the center.

The Greedy Algorithm also showed greater variability in its results, with a standard deviation of approximately 7.66 m, as opposed to the Genetic Algorithm's standard deviation of approximately 5.86 m. This greater spread is reflected in the broader interquartile range (IQR), which goes from approximately 53.81 m to 61.71 m for the Greedy Algorithm, compared to the Genetic Algorithm's IQR from approximately 45.58 m to 53.08 m. The minimum and maximum values indicate the range of the data, with the Greedy Algorithm ranging from 36.15 m to 74.3 m and the Genetic Algorithm ranging from 31.79 m to 61.11 m.

In summary, the Greedy Algorithm not only averaged higher total flight route lengths but also had a wider range of outcomes, suggesting less consistency in the flight route lengths it produced compared to the Genetic Algorithm.

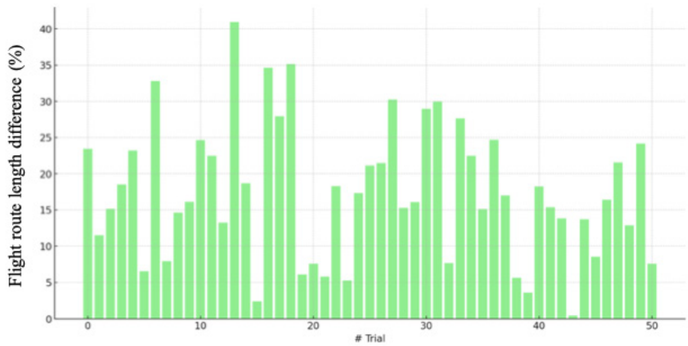


Figure 6. Flight route length difference of greedy algorithm compared to genetic algorithm

The bar plot shows the percentage difference in flight route lengths between the Greedy and Genetic algorithms across a series of trials (Figure 6). Each bar corresponds to a single trial, and the height represents the percentage by which the flight length of the greedy algorithm is greater or less than that of the genetic algorithm for that trial. The average percentage difference across all trials was approximately 17.44 %, indicating that, on average, the flight distance of the greedy algorithm was approximately 17.44 % longer than that of the Genetic algorithm.

Overall, these statistics suggest that, although the Genetic Algorithm generally outperforms the Greedy Algorithm in finding shorter flight routes in every trial, the extent of this advantage can vary. In some cases, the Greedy Algorithm approached the efficiency of the Genetic Algorithm, there were instances where the greedy algorithm was much less efficient. This was because of the stochastic nature of the simulation environment.

After conducting a statistical analysis comparing the flight route lengths of the Greedy and Genetic algorithms, we first assessed the normality of the data. The

Shapiro-Wilk test returned p-values of 3.03×10^{-1} for the Greedy Algorithm and 5.02×10^{-1} for the Genetic Algorithm, both well above the 0.05 threshold, suggesting that the data for both algorithms are normally distributed. Next, we evaluated the homogeneity of variances using Levene's test, which yielded a p-value of 1.61×10^{-1}, indicating no significant difference in variances between the two groups. Because the dataset satisfied the criteria of normal distribution and homogeneity of variance, we applied the t-test to check if there was a statistical difference between the flight routes created by both algorithms. An independent samples t-test was performed, resulting in a p-value of approximately 7.18×10^{-9} and a t-statistic of 6.325, indicating a statistically significant difference in the flight distances generated by the two algorithms. The analysis implies that the Greedy Algorithm consistently produces longer flight distances than Genetic Algorithm, with a high degree of statistical significance. This improvement in path efficiency can translate into substantial cost savings and operational efficiency in a real-world agricultural context.

The GA's ability to explore a diverse set of potential solutions and its use of evolutionary operators allows it to avoid local optima and discover more efficient routes (Niu et al., 2020). Over the course of 500 generations, the GA demonstrated a clear convergence towards optimal solutions, as evidenced by the decreasing trend in the fitness values of the population.

The Greedy Algorithm, while faster in producing a solution, does not have mechanisms to escape local optima, leading to suboptimal paths (Li et al., 2022). The heuristic of choosing the nearest next point did not account for the overall route efficiency, which resulted in a longer total length when all points were visited.

The results underscore the effectiveness of GAs in solving complex optimization problems, such as route planning for drones in precision agriculture (Mukhamediev et al., 2023; Zou et al., 2023). The 17.44 % reduction in route length by GA can lead to reduced fuel or battery consumption, lower labor costs, and a decrease in the time required to complete the spraying operations (Basiri et al., 2022). These factors are critical in large-scale farming operations where efficiency gains can lead to significant economic and environmental benefits (Edwards, 2020; Delay et al., 2022).

However, it is important to note that the GA requires a more substantial computational effort than the Greedy Algorithm. The trade-off between the solution quality and computational resources is a key consideration in the practical application of these algorithms. For time-sensitive applications, a hybrid approach can be considered, where the Greedy Algorithm provides a quick initial solution that the GA can further refine in more time. Alternatively, the method can be employed for offline route planning for agricultural drones, as demonstrated in scenarios in which a pre-existing application map is available.

The study also opens up avenues for future research, such as the integration of real-time data to dynamically adapt the flight route to changing field conditions or the application of other metaheuristic algorithms that could offer a better balance between solution quality and computational time.

In conclusion, while the GA provided a more efficient solution in terms of route length, the choice of algorithm should be guided by the specific requirements of the agricultural operation, including the size of the field, urgency of the task, and available computational resources.

4. CONCLUSION

This study demonstrated the utility of Genetic Algorithms (GA) in optimizing drone flight routes for agricultural spraying, achieving a 17.44 % reduction in the average route length compared with the Greedy Algorithm. The robustness of the GA in finding near-optimal solutions highlights its potential for enhancing operational efficiency in precision agriculture, leading to reduced resource consumption and time savings.

Despite these promising results, this study has some limitations. The primary constraint lies in the computational demands of GA, which may limit its real-time application in the field. The simulation was conducted on a static field model, which does not account for dynamic environmental factors, such as changing weather conditions, variable crop growth stages, or unexpected obstacles that could affect the drone's flight route.

However, the computational intensity of genetic algorithms (GA) is less of a hindrance when applied to offline route planning for agricultural drones. With pre-mapped application fields, GA can be executed on powerful computers without the urgency of real-time decision-making, allowing for detailed and extensive optimization processes. This offline planning enabled the algorithm to incorporate complex field data, historical patterns, and predictive models to devise highly efficient flight paths. Consequently, drones can be deployed with pre-optimized routes that maximize coverage and efficiency, significantly benefiting resource management while mitigating the risks associated with dynamic in-field variables. Another limitation is the reliance of the study on a binary representation of spray areas, which may oversimplify the complexity of actual agricultural landscapes.

Furthermore, this study did not consider the energy consumption of the drone during flight, which could be a significant factor in the practical implementation of flight paths. Future research could incorporate a more detailed energy model and test the algorithms in a dynamic and realistic setting.

In conclusion, while the GA shows significant promise for improving the efficiency of agricultural drone operations, its practical application requires addressing computational challenges and considering the complexities of real-world agricultural environments. Future studies should aim to refine the algorithms to handle dynamic and complex conditions better, potentially through the integration of real-time data and adaptive path planning capabilities.

Conflict of Interest

The authors declare that there is no conflict of interest.

Ethics

This study does not require ethics committee approval.

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