A Fuzzy Logic-Based Differential Evolution for Energy-Efficient UAV Path Planning

Wang Yukai
Hanyang University
Ansan 15588
South Korea
ykwang
@hanyang.ac.kr

Jian-Yu Li
Hanyang University
Ansan 15588
South Korea
jianyulics
@foxmail.com

Peifa Sun
Hanyang University
Ansan 15588
South Korea
pfsun
@hanyang.ac.kr

Sang-Woon Jeon
Hanyang University
Ansan 15588
South Korea
sangwoonjeon
@hanyang.ac.kr

***Abstract*—Unmanned aerial vehicles (UAVs) are emerging as a critical tool in various real-world applications. However, the path planning of UAVs is still challenging. Since UAVs need to fly to several task spots and complete tasks at each spot, the energy consumption of not only UAV flight but also task execution (such as data collection and processing) should be considered, as it may vary across different spots. Therefore, this paper develops a new path planning model for UAVs and proposes a novel fuzzy logic-based differential evolution algorithm that provides efficient path planning while ensuring minimal energy consumption.**

I. Introduction

Recently, unmanned aerial vehicles (UAVs) have been actively utilized in diverse fields such as environmental tracking, urban development, and public safety. Equipped with sensors and cameras, they gather invaluable information, contributing to the management of our surroundings and societies [1], [2]. Along with the growing significance of UAVs, reducing the energy consumption of UAV path planning and task execution is crucial for enhancing UAVs' operating time, lifespan, and efficiency, while also minimizing ecological impact and expenses [3]. Even thought UAV path planning has garnered significant attention in both academia and industry [4], there has been limited focus on planning paths for energy-efficient UAVs that consider both flight and task execution. In this paper, we introduce a path planning model to design energy-efficient UAV routes. However, being an NP-hard problem [5], [6] and further complicated by energy considerations, it poses a challenge to conventional optimization methods like the shortest path algorithm [7]. We address this challenge by employing differential evolution (DE) [8], a powerful tool suited for tackling complex problems of this nature.

Although DE performs well in traditional optimization scenarios [9], it falls short in the context of energy-efficient UAV path planning due to additional complexities. To tackle this challenge, we enhance DE with fuzzy logic [10], making it well-suited for addressing this specific problem. In particular, we utilize fuzzy logic to guide mutations, enabling faster convergence and improve optimization outcomes.

II. Problem Formulation

In this paper, we consider a rotary-wing UAV operating within a 2D environment. This environment comprises M sites: a central hub for UAV departure/return and $(M-1)$ task locations. The UAV is capable of handling $M-1$ tasks, and our objective is to develop an energy-efficient plan, which involves selecting N $(1 < N \leq M)$ locations, including the obligatory UAV center. The selection of task sites depends on the level of data detail required; a higher value of N implies detailed data, whereas a lower value of N provides a broader overview. The UAV's energy consumption is divided into two components: flight consumption, denoted as c_α, and task-related consumption, denoted as c_β, each with corresponding weights ω_α and ω_β to indicate their respective significance.

The objective of this study is to identify a loop within the graph, commencing and concluding at the initial vertex, with the vertex count equal to N. We define $\boldsymbol{X} \in \{0,1\}^{M\times M}$ as the adjacency matrix to represent the UAV's task spot visits, which is reprensented hy

$$\boldsymbol{X} = \begin{bmatrix} x_{(1,1)} & x_{(1,2)} & \cdots & x_{(1,M)} \\ x_{(2,1)} & x_{(2,2)} & \cdots & x_{(2,M)} \\ \vdots & \vdots & \ddots & \vdots \\ x_{(M,1)} & x_{(M,2)} & \cdots & x_{(M,M)} \end{bmatrix}_{M\times M}, \tag{1}$$

where $x_{(i,j)} = 1$ denotes that the UAV travels from the ith task spot to the jth task spot, whereas $x_{(i,j)} = 0$ signifies that the UAV does not make the journey from the ith task spot to the jth task spot. Notably, the first row of $\boldsymbol{X}$ signifies the path from the UAV center to various task spots, while the first column indicates the route from any given task spot back to the UAV center. Let us define a vector $\boldsymbol{r} = [r_1, r_2, \ldots, r_{N+1}] \in \mathbb{N}+^{1\times(N+1)}$ to encapsulate the route, where both r_1 and r_{N+1} are assigned the value 1, and $r_n = j$ if $x_{(r_{n-1},j)} = 1$ for all $n \in \{2, 3, \ldots, N\}$.

Then, the total energy consumption can be calculated by

$$C = \sum_{i=1}^{N}\sum_{j=1}^{N} x_{(i,j)} * (\omega_\alpha * c_{\alpha,i} + \omega_\beta * c_{\beta,(i,j)}), \tag{2}$$

where $c_{\alpha,i}$ is the energy consumption required for the task execution in the ith task spot and the $c_{\beta,(i,j)}$ is the energy consumption of flying from the ith task spot to the jth task spot.

Note that minimizing C in (2) corresponds to a classical 0-1 planning optimization problem, where the elements of $\boldsymbol{X}$ are the decision variables and (2) is the objective function f

$(f : \{0,1\}^{M\times M} \to \mathbb{R})$. According to our consideration, this optimization problem can be written as

$$\min_{\boldsymbol{X}} f(\boldsymbol{X}) = \sum_{i=1}^{N}\sum_{j=1}^{N} x_{(i,j)} * (\alpha * c_{\alpha,i} + (1-\alpha) * c_{\beta,(i,j)}). \tag{3}$$

In Section III, we propose a fuzzy logic-based differential evolution algorithm that provides efficient path planning while ensuring minimal energy consumption.

III. Methodology

A. Matrix-Based Encoding and Individual Vector Design

In the studied problem, the solution is encoded using an adjacency matrix. Representing the adjacency matrix as an individual vector would result in an excessive number of dimensions. Therefore, we directly employ the adjacency list as an individual vector:

$$\boldsymbol{x}_i^g = \left[x_{(i1)}, x_{(i2)}, \ldots, x_{(iM)}\right]. \tag{4}$$

B. Fuzzy Logic-Based Individual Selection

Fuzzy logic, a system skilled at managing uncertainty issues, leverages fuzzy sets and rules for non-correlated target reasoning [11]. This helps solve problems with unclear boundaries, differentiating values of fuzzy sets using membership functions. This research targets two optimization objectives: flying distance consumption and task consumption. Utilizing the population's extreme values, we establish the membership function for each target using two thresholds:

$$\begin{aligned} fly_{min} &= x_{flymin} \times (1+\varepsilon), \\ fly_{max} &= x_{flymax} \times (1-\varepsilon), \\ task_{min} &= x_{taskmin} \times (1+\varepsilon), \\ task_{max} &= x_{taskmax} \times (1-\varepsilon), \end{aligned} \tag{5}$$

where ε is a scaling parameter. Here, fly_{min} and fly_{max} are used as the fuzzy variable threshold of flying distance, $task_{min}$ and $task_{max}$ are used as the fuzzy variable threshold of task consumption, and U_1 and U_2 signify the membership degrees of flying distance and task consumption respectively. Then we define U_1 and U_2 as

$$U_1 = \begin{cases} 0, & \text{if } x_{\text{fly}} \le \text{fly}_{\text{min}}, \\ \frac{1}{\text{fly}_{\text{max}} - \text{fly}_{\text{min}}} \times (x_{\text{fly}} - \text{fly}_{\text{min}}), & \text{if } \text{fly}_{\text{min}} < x_{\text{fly}} < \text{fly}_{\text{max}}, \\ 1, & \text{otherwise,} \end{cases}$$

$$U_2 = \begin{cases} 0, & \text{if } x_{\text{task}} \le \text{task}_{\text{min}}, \\ \frac{1}{\text{task}_{\text{max}} - \text{task}_{\text{min}}} \times (x_{\text{task}} - \text{task}_{\text{min}}), & \text{if } \text{task}_{\text{min}} < x_{\text{task}} < \text{task}_{\text{max}}, \\ 1, & \text{otherwise.} \end{cases} \tag{6}$$

By Adding the above two values, we define U_{all} as

$$U_{all} = \omega_\alpha \times U_1 + \omega_\alpha \times U_2. \tag{7}$$

Here, U_{all} is used as the degree of membership of the entire planning problem. Then, for every $\boldsymbol{x}_i^g$, U_{all} can be generated and constructed $\boldsymbol{U}_{all}$ by gathering for all possible $\boldsymbol{x}_i^g$.

Next, we sort $\boldsymbol{U}_{all}$ in ascending order to construct $\boldsymbol{U}_{allasc}$. We define

$$\boldsymbol{I}_{preferable} = \boldsymbol{U}_{allasc}[:\lceil \text{len}(\boldsymbol{U}_{allasc}) \times \text{ratio}\rceil], \tag{8}$$

where ratio $\in (0,1)$ is a predetermined value and $\mathbf{A}[:a]$ is the vector consisting of the first a elements in $\mathbf{A}$ for $a \le \text{len}(\mathbf{A})$.

Note that better individuals in $\boldsymbol{U}_{allasc}$ consists of $\boldsymbol{I}_{preferable}$. This makes $\boldsymbol{I}_{preferable}$ a collection of superior solutions. During the mutation step in DE, $\boldsymbol{x}_1$, $\boldsymbol{x}_2$, $\boldsymbol{x}_3$ are randomly chosen from the whole population. In our FDE, $\boldsymbol{x}_2$'s selection area is indicated as the $\boldsymbol{I}_{preferable}$.

C. Fuzzy Logic-Based Differential Evolution Algorithm

We propose a fuzzy logic-based DE (FDE) Algorithm to optimize the problem in (3). The proposed FDE consists of four main operators: Population initialization, mutation, crossover, and selection. Define P as the population size and D as the dimension size.

Population initialization: DE is a population-based optimization algorithm, the population of which improves and evolves following the difference between individuals. The first step of DE is to initialize the population with random numbers as

$$\boldsymbol{x}_{i,j}^g = L_j + Rand \times (U_j - L_j), \tag{9}$$

We then convert (4) into path vectors, applying the feasibility principle to constrain the individuals [12].

Mutation: At the gth generation, each target vector $\boldsymbol{x_i^g}$ will generate the corresponding mutant $\boldsymbol{v_i^g}$, also called donor vector, following the operator shown below:

$$\boldsymbol{v}_i^g = \boldsymbol{x}_{r_1}^g + F \times (\boldsymbol{x}_{r_2}^g - \boldsymbol{x}_{r_3}^g), \tag{10}$$

where r_1 and r_3 are two different random integers sampled from $\{1,2,3,\ldots,P\}$, the value of r_2 is different from the other two. The selection range for r_2 is $\boldsymbol{I}_{preferable}$ and also not identical to the index i. The amplification factor F is often valued from $[0,1]$, controls the overall size of the individual difference. Each dimension of individuals has to be within the search space $[L_j, T_j]$. If not, we use (11) to adjust the value of each dimension:

$$v_{i,j}^g = \begin{cases} L_j, & v_{i,j}^g < L_j, \\ T_j, & v_{i,j}^g > T_j. \end{cases} \tag{11}$$

Crossover: After mutation, the algorithm will implement the calculation of the crossover operator (usually using the version of binomial) with $\boldsymbol{x}_i^g$ and $\boldsymbol{v}_i^g$ to generate the trial vector $\boldsymbol{u}_i^g$ as

$$u_{i,j}^g = \begin{cases} v_{i,j}^g, & (rand \le CR) \vee (j = j_{rand}), \\ x_{i,j}^g, & \text{otherwise,} \end{cases} \tag{12}$$

where CR is the crossover rate parameter.

Selection: The last operator is selection determining whether trail vector $\boldsymbol{u}_i^g$ or target vector $\boldsymbol{x}_i^g$ can go to the next generation. For minimization problem, in this operation, $\boldsymbol{x}_i^g$ and $\boldsymbol{u}_i^g$

will be compared to the fitness of each other, thereby choosing the better one to enter the next generation as

$$\boldsymbol{x}_i^{g+1} = \begin{cases} \boldsymbol{u}_i^g, & f(\boldsymbol{u}_i^g) \le f(\boldsymbol{x}_i^g), \\ \boldsymbol{x}_i^g, & f(\boldsymbol{u}_i^g) > f(\boldsymbol{x}_i^g), \end{cases} \tag{13}$$

where f is the fitness function.

IV. Performance Evaluation

A. Simulation Data and Experiment Setting

Task spots near the center result in higher transmission and reception consumption, while those situated farther away require lower consumption. Conversely, visiting remote task spots raises the UAV's flight consumption, despite potential lower task consumption. We have generated data to emulate this scenario, involving 10 designated locations labeled as the center, task spot A through I. The UAV initiates its tasks from the center and returns upon completion. Task spots are positioned within a $[0, 250] \times [0, 250]$ map.

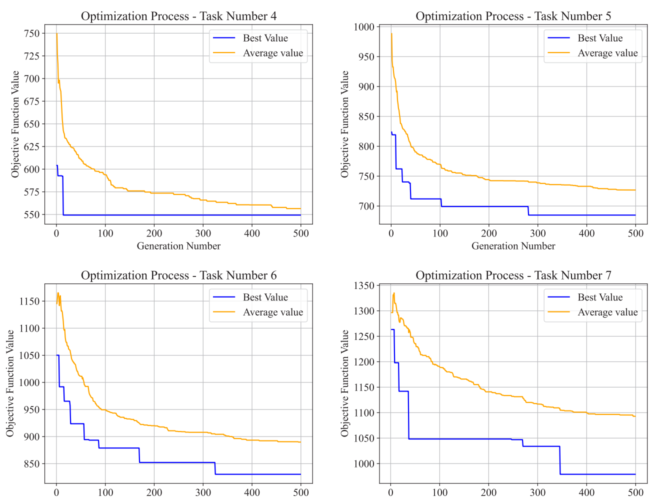

Fig. 1. Optimization process on task number 4, 5, 6, and 7.

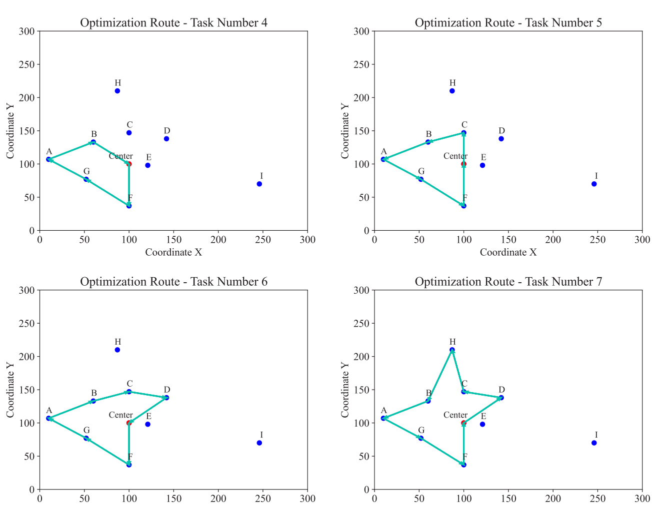

Fig. 2. Path planning on task number 4, 5, 6, and 7.

B. Simulation Results

Fig. 1 illustrates the average and best values for 4 to 7 selected tasks of the proposed FDE and Fig. 2 illustrates the path planning aimed at minimizing the total consumption for these tasks. The convergence of the average value to the best value over iterations signifies the evolutionary progress of the population towards a minimum. Although the best value emerges later as the number of tasks increases, the optimal value is still achieved before the 500th iteration.

V. Conclusion

In this paper, we explored a scenario involving UAVs completing specific tasks and presented the novel FDE algorithm to tackle the intertwined issues of path planning and resource allocation. Our results showed that the optimization efficiency provided by the proposed FDE surpasses the standard DE, although challenges remain in applying fuzzy logic to more complex systems, suggesting future avenues for research.

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References

[1] Y. Song, S. H. Lim, S.-W. Jeon, and S. Baek, "On cooperative achievable rates of UAV assisted cellular networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 9, pp. 9882–9895, 2020.

[2] M. S. Haroon, S. H. Chae, and S.-W. Jeon, "Outage analysis for multi-radio heterogeneous networks in the presence of aerial jammers," to appear in *ICT Express,* 2023.

[3] M. Yang, S.-W. Jeon, and D. K. Kim, "Optimal trajectory for curvature-constrained UAV mobile base stations," *IEEE Wireless Communications Letters*, vol. 9, no. 7, pp. 1056–1059, 2020.

[4] R.-J. Wai and A. S. Prasetia, "Adaptive neural network control and optimal path planning of uav surveillance system with energy consumption prediction," *IEEE Access*, vol. 7, pp. 126 137–126 153, 2019.

[5] J. Chen, C. Du, Y. Zhang, P. Han, and W. Wei, "A clustering-based coverage path planning method for autonomous heterogeneous UAVs," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 12, pp. 25 546–25 556, 2022.

[6] M. Kang and S.-W. Jeon, "Energy-efficient data aggregation and collection for multi-UAV-enabled IoT networks," in revision for *IEEE Wireless Communications Letters*.

[7] R. W. Floyd, "Algorithm 97: Shortest path," *Communications of the ACM*, vol. 5, no. 6, p. 345, 1962.

[8] J.-Y. Li, Z.-H. Zhan, K. C. Tan, and J. Zhang, "A meta-knowledge transfer-based differential evolution for multitask optimization," *IEEE Transactions on Evolutionary Computation*, vol. 26, no. 4, pp. 719–734, 2021.

[9] W. Deng, S. Shang, X. Cai, H. Zhao, Y. Song, and J. Xu, "An improved differential evolution algorithm and its application in optimization problem," *Soft Computing*, vol. 25, pp. 5277–5298, 2021.

[10] S. Trigui, O. Cheikhrouhou, A. Koubaa, U. Baroudi, and H. Youssef, "FL-MTSP: A fuzzy logic approach to solve the multi-objective multiple traveling salesman problem for multi-robot systems," *Soft computing*, vol. 21, pp. 7351–7362, 2017.

[11] L. A. Zadeh, "Fuzzy logic," in *Granular, Fuzzy, and Soft Computing*. Springer, 2023, pp. 19–49.

[12] K. Deb, "An efficient constraint handling method for genetic algorithms," *Computer methods in applied mechanics and engineering*, vol. 186, no. 2-4, pp. 311–338, 2000.