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Intelligent Decision Making Approach for Multi-Criteria Path Planning of Unmanned Aerial Vehicles

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Abstract— **This paper proposed a new methodology to determine the optimal trajectory for an Unmanned Aerial Vehicle (UAV) based on a Multiobjective multi-verse algorithm. The main objective of the formulated problem is to get a short and smooth path with an acceptable altitude by avoiding all obstacles. The Technique for Order Preference by Similarity to Ideal Situation (TOPSIS) is used to select the best solution in the sense of Pareto optimization. Several classical Multi-Criteria Decision Making (MCDM) methods are used as comparison tools. In order to compare the rankings obtained from the reported MCDM methods, the Spearman's rank correlation and Kendall's coefficients are used to show their differences and similarities. The obtained results, conducted by numerical simulations, are satisfactory and promising.**

***Keywords*— Unmanned aerial vehicles, trajectories planning, multiobjective multi-verse optimizer (MOMVO), Technique for Order Preference by Similarity to Ideal Situation (TOPSIS).**

I. INTRODUCTION

In recent years, the path planning problem for UAVs is one of the most significant research themes in the field of aerial robotics. Many approaches have been proposed to solve such a complex problem. Among the classical approaches, the most representative ones are the Voronoi diagram searching method [1], A* algorithm [2], potential field approaches [3], and so on. These methods have some advantages, but most of them are expensive and can be trapped in local minima [4]. As a promising alternative for improving these methods, the metaheuristic algorithms overcome these shortcomings.

Since multiple criteria should be treated simultaneously in the UAVs' path planning problem, the multiobjective metaheuristics are used to solve such a problem. In [5], the authors have used the multi-objectives genetic algorithms to solve the complex multi-UAVs path planning problems. The authors in [6] have proposed the crowding distance based NSGA-II algorithm to find an optimal path without collision for UAVs in an urban environment. In [7], the convergence rate of the multiobjective evolutionary algorithm is reduced using weighted random strategies. The authors in [8] have used an improved multi-objective artificial bee colony algorithm to solve the UAVs' path planning problem by maintaining a short, safe and smooth path.

Based on aforementioned studies, the main contribution of this paper is to propose a constrained Multiobjective Multi-Verse Optimizer (MOMVO) to solve the path planning problem for UAVs. The proposed MOMVO-based approach leads to a set of non-dominated solutions where the choice of the best solution requires a higher-level decision-making approach. The Technique for Order Preference by Similarity to Ideal Situation (TOPSIS) is proposed. The well-known Multi Criteria Decision Making (MCDM) methods as ‘‘VlseKriterijumska Optimizacija I Kompromisno Resenje’’ (VIKOR), Weighted Sum Model (WSM), Simple Average Weight (SAW) and Evaluation Based on Distance from Average Solution (EDAS) are used as comparison tools to show the superiority of the proposed TOPSIS-based strategy.

The remainder of this paper is organized as follows. In Section II, the path planning problem is formulated as a multiobjective optimization problem under nonlinear and hard operational constraints. In Section III, the proposed MOMVO algorithm is introduced. In Section IV, the TOPSIS technique is described. In Section V, the simulation results are given and discussed in order to show the effectiveness and superiority of the proposed TOPSIS/MOMVO-based path planning approach. Section VI concludes this paper.

II. PROBLEM FORMULATION

A. Terrain modelling

In a real navigation environment, it is very challenging to define the geometric coordinates of the obstacles. For minimizing the measurement errors, the models must be fully integrating the real obstacles. In this work, an environment with static menaces that are characterized by cylinder models is considered as shown in Fig.1. The two points S and P, which have the coordinates (x_1, y_1, z_1) and (x_n, y_n, z_n), respectively, are considered as a starting and arrival points. The waypoints are on the perpendicular planes $(L_1, L_2, L_3, .., L_n)$ that are passed by the division points defined as $x_1, x_2, x_3, \ldots, x_n$. These corresponding points are obtained by dividing the x-axis range (x_1, x_n) into $n-1$ equal segments.

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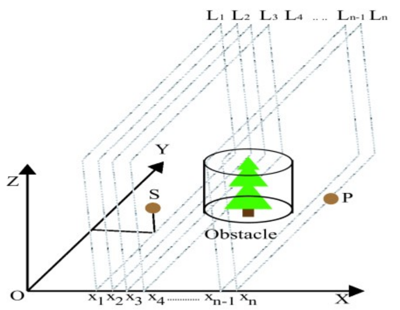

Fig. 1. Modelling of the flight environment.

A sequence of waypoints $C=\{S,(x_2,y_2,z_2),...,(x_{n-1},y_{n-1},z_{n-1}),P\}$ is then formed. These waypoints are connected to obtain a smooth path. The x-coordinates of all waypoints are know but their y-coordinates and z-coordinates have to be optimized to find the optimal path. In this manner, the path planning problem is transformed as an optimization problem with $\boldsymbol{\theta}=\{\theta_i\}_{2\leq i\leq n-1}=[y_2,y_3,...,y_{n-1},z_2,z_3,...,z_{n-1}]$ as decision variables.

B. Objective functions

The general form of a multiobjective optimization problem is defined as follows [9]:

$$\begin{cases} \underset{\boldsymbol{\theta}\in\boldsymbol{D}\subseteq\mathbb{R}^q}{\text{Minimize}}\, F(\boldsymbol{\theta})=\{f_1(\boldsymbol{\theta}),f_2(\boldsymbol{\theta}),\dots f_m(\boldsymbol{\theta})\} \\ \text{s.t:} \\ g_v(\boldsymbol{\theta})\leq 0 \quad v=1,2,...,V \\ h_w(\boldsymbol{\theta})=0 \quad w=1,2,...,W \\ \boldsymbol{\theta}\in\boldsymbol{D}\subseteq \mathrm{R}^q \end{cases} \tag{1}$$

where $f_j:\mathbb{R}^q\rightarrow\mathbb{R}$, $j=1,2,\dots,m$, denote the j[th] objective function, $\boldsymbol{D}=\{\boldsymbol{\theta}\in\mathbb{R}^q,\boldsymbol{\theta}_{\min}\leq\boldsymbol{\theta}\leq\boldsymbol{\theta}_{\max}\}$ is the bounded search domain and $g_v:\mathbb{R}^q\rightarrow\mathbb{R}$ and $h_w:\mathbb{R}^q\rightarrow\mathbb{R}$ are the inequality and equality constraints, respectively.

The objective functions which can be considered for the path planning process are related to the path length and the flight altitude. The first objective function to be minimized in problem (1) is chosen as follows:

$$f_1(\boldsymbol{\theta})=\frac{\sum_{k=1}^{n-1}\sqrt{(x_{k+1}-x_k)^2+(y_{k+1}-y_k)^2+(z_{k+1}-z_k)^2}}{\sqrt{(x_n-x_1)^2+(y_n-y_1)^2+(z_n-z_1)^2}} \tag{2}$$

The second objective function is the flying altitude. It is desirable that the UAV flies between a minimum and maximum flying heights. The objective function associated with the altitude of the path is so chosen as follows:

$$f_2(\boldsymbol{\theta})=\begin{cases} \dfrac{Z_{\max}-A_{avr}}{Z_{\max}-Z_{\min}} & \text{if } A_{avr}<Z_{\min} \\ \dfrac{A_{avr}-Z_{\min}}{Z_{\max}-Z_{\min}} & \text{if } A_{avr}>Z_{\max} \end{cases} \tag{3}$$

where $Z_{\min}$ and $Z_{\max}$ are the lower and upper limits of the flying altitude, respectively, and A_{avr} is the average value of $\sigma=[z_2,z_3,...,z_{n-1}]$.

The flight path should pass neither inside the danger regions nor over it to avoid the risk of being detected by radars. Thus, such an avoidance constraint can be expressed as follows:

$$g_1(\boldsymbol{\theta})=\sqrt{(x_u-x_i)^2+(y_u-y_i)^2}-(r_i+\delta)\leq 0 \tag{4}$$

where (x_u,y_u,z_u) means the coordinates of the UAV drone, (x_i,y_i,z_i,r_i) is the coordinates vector of the i[th] obstacle zone, (x_i,y_i) means the center on the XOY plane, r_i is the detected range and δ presents the safety distance.

When the UAV moves along a uniform rectilinear path, the burden can be reduced and the flight efficiency of the UAV can be ensured. In order to maximize the straightness of the path, the angle between two given adjacent segments $\varphi_{i,j}$ is introduced. This performance constraint is illustrated by the following expression:

$$g_2(\boldsymbol{\theta})=|\varphi_{i,j}|-\varphi_{\max}\leq 0 \tag{5}$$

where $\varphi_{\max}$ is the maximum value of the driving angle and $i=1,2,\dots,n-1;\ j=1,2,\dots,m$.

Finally, the constrained optimization problem formulated for the UAV path planning is given as follows:

$$\begin{cases} \underset{\boldsymbol{\theta}\in\boldsymbol{D}\subseteq\mathbb{R}^{n-2}}{\text{Minimize}}\, F(\boldsymbol{\theta})=\{f_1(\boldsymbol{\theta}),f_2(\boldsymbol{\theta})\} \\ \text{s.t:} \\ g_1(\boldsymbol{\theta})\leq 0 \\ g_2(\boldsymbol{\theta})\leq 0 \\ \boldsymbol{\theta}\in\boldsymbol{D}\subseteq \mathrm{R}^{n-2} \end{cases} \tag{6}$$

To handle with these operational constraints of (6), the following static penalty function is used [10]:

$$\phi_j(\boldsymbol{\theta})=f_j(\boldsymbol{\theta})+\sum_{v=1}^{V}\lambda_v\max\{0,g_v(\boldsymbol{\theta})\}^2 \tag{7}$$

where $\lambda_v\in\mathbb{R}^+$ is the penalty parameter associated to the v^{th} constraint.

III. Proposed Multiobjective Multi-Verse Optimizer

The Multi-Verse Optimizer (MVO), proposed by Mirjalili et al. [11], is a recent metaheuristic based on the physics theories about the existence of multi-verse. The interaction among different universes is ensured based on the concepts of white/black holes and worm holes. The optimization process of the MVO begins with a set of randomly solutions. The objects from one universe move according to their inflation rates to another via the white/black holes, and displace within a universe or to another via a worm hole [11].

The main updating equations in the MVO process are given as follows [11]:

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Vol.64, pp. 2-9

$$x_i^j = \begin{cases} \begin{cases} x_j + TDR + \left(ub_j - lb_j \times r_4 + lb_j\right) & r_3 < 0.5 \\ x_j + TDR - \left(ub_j - lb_j \times r_4 + lb_j\right) & r_3 < 0.5 \end{cases} & r_2 < WEP \\ x_i^j & r_2 \geq WEP \end{cases} \quad (8)$$

where x_i^j denotes the jth component of the ith solution, x_j indicates the jth variable of the best universe, TDR means the travelling distance rate, WEP is the worm hole existence probability, lb_j and ub_j are the lower and upper bounds, respectively, r_2, r_3 and r_4 are random numbers in [0, 1].

In order to develop a multiobjective version of the MVO metaheuristic, i.e. MOMVO, a concept of the archive is added to its research mechanism [12]. The solutions of the MOMVO are enhanced using black, white and worm holes. For selecting solutions from the archive, a leader selection mechanism is implemented to establish tunnels among solutions. A roulette wheel approach is used to select the fittest solutions. Obviously, a limited number of solutions can be accommodated in the archive. In order to remove the unsatisfactory ones, a probabilistic mechanism given as:

$$P_i^{'} = {N_i}/{c} \quad (9)$$

where N_i defines the number of the vicinity solutions and c is a constant which is greater than 1.

IV. Decision Model

Since the path planning problem is multi-criteria, the recourse of a decision making method remains essential [13]. In this paper, the TOPSIS technique is used to solve such a problem. The TOPSIS is one of the most widely used MCDM models that consist of the following steps [13,14]:

Step 1: If n is the number of alternatives and m is the number of criteria, a decision matrix will be obtained as follows:

$$D = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}; \; x_{ij}\left(i=1,2,\ldots n,\; j=1,2,\ldots m\right) \quad (10)$$

Step 2: The normalized values x_{ij} of Eq. (10) are obtained as follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}} \quad (11)$$

Step 3: Calculate the weighted normalized decision matrix as follows:

$$v_{ij} = w_i \times r_{ij} \qquad j = 1,2,\ldots m, \quad i = 1,2,\ldots n. \quad (12)$$

where w_i is the weight of the ith criterion, $\sum_{i=1}^{n} w_i = 1$.

Step 4: Find the positive- and negative-ideal solutions:

$$A^+ = \left(v_1^+, v_2^+, \ldots, v_n^+\right) \quad (13)$$

$$A^- = \left(v_1^-, v_2^-, \ldots, v_n^-\right) \quad (14)$$

Step 5: Calculate the n-dimensional Euclidean distance as follows:

$$d_j^+ = \sqrt{\sum_{i=1}^{n}\left(v_{ij} - v_j^+\right)}, \quad j = 1,2,\ldots,m. \quad (15)$$

$$d_j^- = \sqrt{\sum_{i=1}^{n}\left(v_{ij} - v_j^-\right)}, \quad j = 1,2,\ldots,m. \quad (16)$$

Step 6: Calculate the relative closeness to the ideal solution as:

$$C_j = \frac{d_j^-}{d_j^+ + d_j^-}, \qquad j = 1,2,\ldots,n. \quad (17)$$

Step 7: Choose an alternative with maximum C_j or rank alternatives according to C_j in descending order.

V. Simulation Results and Discussions

The control parameters retained for the proposed MOMVO algorithm are given as follows: max of iterations $N_{iter} = 100$, population size $N_{pop} = 50$, min and max of wormhole existence probabilities 0.2 and 1. The TOPSIS method is adopted for the UAVs' path planning problem (6). In order to evaluate the performance of such a proposed MCDM method, others techniques such as VIKOR [15], WSM [16], SAW [17] and EDAS [18] are considered for a comparative study. MATLAB 7.8 environment is considered as the software tool operating on a PC with i7 Core 2 Duo/2.67 GHz CPU and 6.00 GB RAM.

In order to evaluate the performance of the proposed decision making method, a simulation scenario with six threads is included and many metrics are used as performance criteria. Figure 2 shows the optimal Pareto front obtained by the proposed MOMVO algorithm as well as the optimal points selected by the reported MCDM methods.

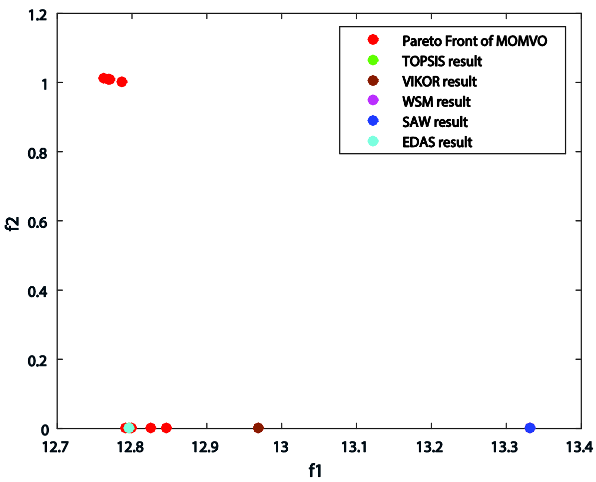

Fig 2. Optimal Pareto front obtained by MOMVO and best solution selected by different MCDM methods.

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In order to assess the effect of the MCDM methods, the planned paths corresponding to the selected optimal solutions are depicted in Fig. 3.The optimal solution selected by the TOPSIS and EDAS, as well as the WSM and SAW, are the same. The proposed MOMVO algorithm with the selected MCDM methods completes the mission avoiding all the obstacles and the planned path is keeping far from the obstacles. The results corresponding to the path length are presented in Table I. The shortest path is given by the TOPSIS and EDAS methods.

TABLE I
PATH LENGTH OBTAINED BY DIFFERENT MCDM METHODS

Criterion	TOPSIS	VIKOR	WSM	SAW	EDAS
Path length	**12.854**	13.046	13.565	13.565	**12.854**

Table II presents the set of non-dominated solutions given by the proposed MOMVO algorithm and the ranking patterns obtained by all MCDM techniques. In order to evaluate the applicability and suitability of the five MCDM methods to solve the planning problem (6), the measure of association between their relative ranking are determined using the following measures: Kendall's coefficient of concordance [19] and Spearman's rank correlation coefficient [20]. The Kendall's coefficient of concordance Q is used to compare the ranking results from the five MCDM methods. Based on the data obtained in Table II, the Kendall's coefficient of concordance value is $Q = 0.5815$. The significance of the concordance coefficient is calculated as follows [21]:

$$\chi^2 = M(N-1)Q \tag{18}$$

TABLE II
RANKING PATTERNS OBTAINED BY DIFFERENT MCDM TECHNIQUES

Pareto Front		MCDM ranking method				
f1	f2	TOPSIS	VIKOR	WSM	SAW	EDAS
13,33199	4,207e-06	7	12	1	1	7
12,96849	1,255e-05	6	1	2	3	6
12,82423	0,00019	3	2	4	4	3
12,79173	0,00129	5	3	7	5	4
12,78643	1,00241	8	11	12	6	8
12,84597	9,205e-05	4	6	3	7	5
12,79648	0,00035	1	4	6	8	1
12,79933	0,00029	2	5	5	9	2
12,76801	1,01058	11	10	9	10	11
12,76287	1,01118	10	7	8	2	12
12,77096	1,00915	9	8	11	11	9
12,76873	1,01052	12	9	10	12	10

For five MCDM methods ($M = 5$), twelve non-dominated solutions ($N = 12$) and a Kendall's coefficient of concordance ($Q = 0.5815$), the concordance coefficient is computed as $\chi^2 = 31.9825$. Using the table of chi-square distribution with degrees of freedom $N-1=11$ and at the confidence level $\alpha = 0.05$, the critical value is $\chi^2_{11,0.05} = 19.68 < \chi^2$. Hence, the null hypothesis H0 is rejected and the different MCDM methods are consistent.

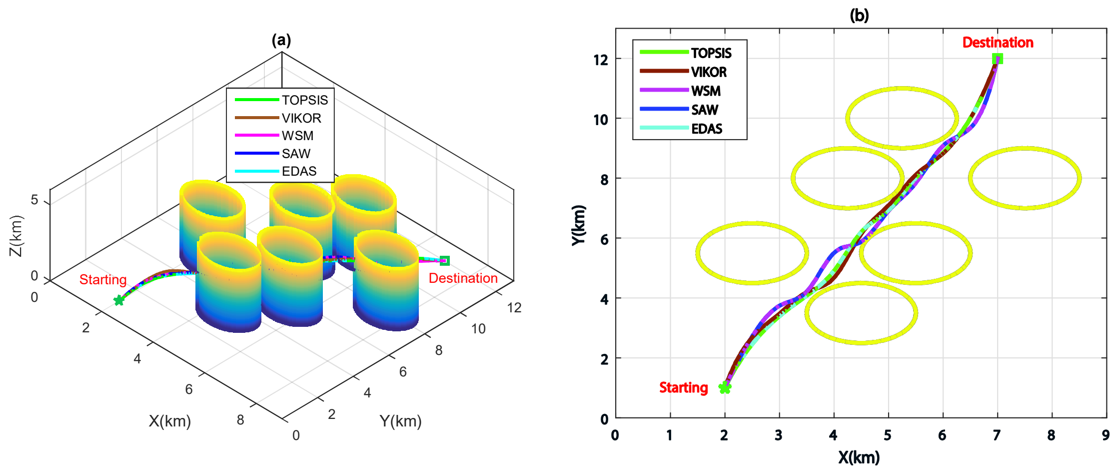

Fig. 3 Performance comparisons for UAV path planning: (a) planned path in 3D, (b) planned path in 2D

The Spearman's rank correlation coefficient r_s is used to measure the similarity between two sets of rankings. When $r_s = 1$, the data pairs have a perfect association between the ranks, when $r_s = -1$ this represents a perfect negative correlation and when $r_s = 0$ it represents no correlation between the ranks. The Spearman's rank coefficients for a set of non-dominated solutions are presented in Table III. In order to test the level of significance of the correlation, we should suppose that there is no correlation between the MCDM methods. The two hypotheses should be stated as: null hypothesis H0 and alternative hypothesis H1. If the calculated value exceeds the critical value, then the hypothesis null is rejected and the correlation is significant. From the table of critical values of Spearman's rank correlation coefficient with a number of data pairs $N = 12$ and at the level of significance $\alpha = 0.05$, the critical value is equal to $(r_s)_{0.05(1),12} = 0.503$.

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TABLE III: SPEARMAN RANK CORRELATION COEFFICIENT VALUES OBTAINED BY DIFFERENT MCDM TECHNIQUES

Methods	TOPSIS	VIKOR	WSM	SAW	EDAS
TOPSIS	1.0000	**0.62937**	**0.56643**	0.20979	**0.96503**
VIKOR		1.0000	0.41258	0.18181	**0.62237**
WSM			1.0000	**0.58741**	**0.51048**
SAW				1.0000	0.08391
EDAS					1.0000

For some cases, the hypothesis null is rejected. We can observe that the TOPSIS method has a significant correlation with the VIKOR, WSM and EDAS methods at the 95% probability level. The SAW method has a significant correlation only with WSM. The EDAS method has a good correlation with the TOPSIS, VIKOR and WSM methods. A highest level of significance of the correlation value of 0.96503 can be observed between TOPSIS and EDAS. The EDAS is very similar to TOPSIS in the correlation level with the others methods. By comparing the TOPSIS and EDAS methods, TOPSIS has the highest correlation level with the VIKOR and WSM methods. The TOPSIS technique presents the most effective technique among the selected MCDM methods to solve considered planning problem (6)-(7).

VI. CONCLUSION

In this paper, a TOPSIS/MOMVO-based approach has been successfully proposed and applied to solve the multi-criteria path planning problem for UAV drones. Such a path planning task has been formulated as a constrained multi-objective optimization problem to have a smooth path with short length and acceptable attitude avoiding all obstacles. The simulation results show the effectiveness of the proposed method compared to the reported algorithms. In future works, our study will be extending to the cooperative multi-UAVs path planning problem with dynamic obstacles.

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