Multi-Criteria Path Planning of Unmanned Aerial Vehicles through a Combined Multi-Verse and Decision Making Methods

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***Abstract*— Paths planning for an Unmanned Aerial Vehicle (UAV) with obstacle avoidance is a multiobjective optimization problem. In this paper, a novel method based on Multiobjective Multi-Verse Algorithm (MOMVO) is presented and successfully implemented to solve the UAV path planning problem. A shortest and smoothest path with an acceptable altitude by avoiding all obstacles is the main objective of the formulated problem. The proposed MOMVO-based method leads to a set of non-dominated solutions. Since decision-making is a necessary task, a Technique for Order Preference by Similarity to Ideal Situation (TOPSIS) is used to select the best solution in the sense of Pareto. Several classical Multi-Criteria Decision Making (MCDM) methods like ''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 compare the rankings obtained from the reported MCDM methods, Spearman's rank correlation and Kendall's coefficients are used to showing their differences and similarities. The Standard Deviation (SD) method is used and compared favourably with other weighting methods for the determination of the weights of the criteria for the TOPSIS technique. The obtained results, conducted by numerical simulations, are satisfactory and very encouraging for future practical implementation.**

***Keywords*— Unmanned Aerial Vehicles, trajectories planning, multi-objective optimization, multiobjective multi-verse optimizer (MOMVO), Technique for Order Preference by Similarity to Ideal Situation (TOPSIS), Standard Deviation (SD).**

I. INTRODUCTION

In recent years, technology has advanced and the labour price has risen. Due to their higher degrees of freedom and working space, unmanned aerial vehicles (UAVs) have unmatchable benefits over terrain robots in various actual applications [1, 2]. The path planning problem for UAVs is one of the most significant research themes in the field of aerial robotics.

In the literature, many approaches have been proposed to solve such a complex optimization problem. Among the classical approaches, the most representative ones are the Voronoi diagram searching method [3], cell decomposition [4], A* algorithm [5], potential field approaches [6], D* lite algorithm [7], and so on. These methods have some advantages, but most of them are expensive and can be trapped in local minima [8]. As a promising alternative for improving these methods, the metaheuristic algorithms overcome these shortcomings. In [9], the authors developed two new hybrid metaheuristics that combine the PSO method both with the genetic algorithm and harmony search algorithm have been proposed to solve the UAVs' path planning problem. In [10], a recent global metaheuristic named Grey Wolf Optimization (GWO) is favourably implemented to solve the UAVs' path planning problem.

Since multiple criteria should be treated simultaneously in the UAVs path planning problem, such as the path's length, smoothness, and safety, these specifications should be treated by multiobjective kind of global metaheuristics. In [11], the authors have used the Multi-Objectives Genetic Algorithms (MOGA) to solve the complex multi-UAVs path planning problems. The authors in [12] have proposed the crowding distance-based NSGA-II algorithm to find an optimal path without collision for UAVs in an urban environment. Two goals such as distance and safety have been considered. In [13], the modified Multi-objective Pigeon-Inspired Optimization (MPIO) is proposed to solve the UAVs path planning task. In [14], the convergence rate of the Multiobjective Evolutionary Algorithm MOEA is reduced using weighted random strategies to solve the multi-UAVs mission planning problem. The authors in [15] 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 the 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 a quadrotor type of UAVs under several flight operational conditions. The proposed MOMVO-based approach leads to a set of non-dominated solutions, with a compromise between the defined objectives. The choice of a solution among all the optimal obtained ones

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in the sense of Pareto 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 standard deviation (SD) method is used and compared favourably with other weighting methods to evaluate the impact of the selected one on the result of the TOPSIS Technique and the final result of the proposed path planning algorithm.

The remainder of this paper is organized as follows. In Section 2, the path planning problem for a UAV is formulated as a multiobjective optimization problem under nonlinear operational constraints. Section 3 presents the proposed MOMVO algorithm to solve the defined path planning problem. In Section 4, the TOPSIS technique is described and used to select the best solution among the set of Pareto non-dominated ones. In Section 5, the simulation results are given and discussed to show the effectiveness and superiority of the proposed SD-TOPSIS/MOMVO-based path planning approach. Section 6 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, a danger zone is characterized by a cylinder model. An environment with static menaces is considered. The UAV path planning problem is to find the optimum or near-optimal path to connect the starting point S and the target point P avoiding all the considered danger zones. The flight environment modelling is depicted in Fig. 1.

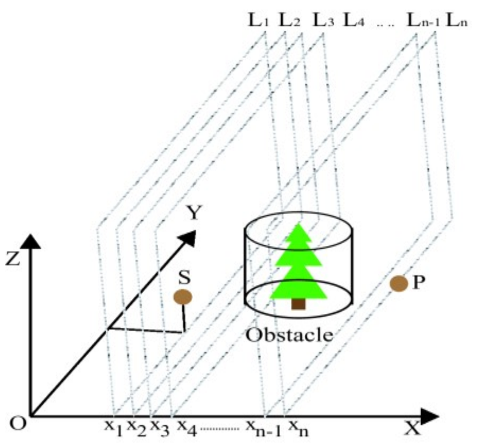

Fig. 1. Modelling of the flight environment.

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 point, respectively. The waypoints are on the perpendicular planes $(L_1, L_2, L_3, \ldots, L_n)$ 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. A sequence of waypoints is then formed as $C = \{S, (x_2, y_2, z_2), \ldots, (x_{n-1}, y_{n-1}, z_{n-1}), P\}$. Based on the cubic Spline interpolation, these waypoints are connected to obtain a smooth path. In this path modelling, the x-coordinates of all waypoints are known 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 into an optimization problem in which the decision variables are defined as $\boldsymbol{\theta} = \{\theta_i\}_{2 \le i \le n-1} = [y_2, y_3, \ldots, y_{n-1}, z_2, z_3, \ldots, z_{n-1}]$.

B. Objective functions

The general form of a multiobjective optimization problem is defined as follows [16]:

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

where $f_j : \mathbb{R}^q \to \mathbb{R}$, $j = 1, 2, \ldots, m$, denote the j^th^ objective function, $\boldsymbol{D} = \{\boldsymbol{\theta} \in \mathbb{R}^q, \boldsymbol{\theta}_{\min} \le \boldsymbol{\theta} \le \boldsymbol{\theta}_{\max}\}$ represents the bounded search domain of the solutions, $g_v : \mathbb{R}^q \to \mathbb{R}$ and $h_w : \mathbb{R}^q \to \mathbb{R}$ are the inequality and equality constraints, respectively, $q \in \mathrm{N}$ is the dimension of the optimization problem, i.e. the number of decision variables.

The objective functions which can be considered for the path planning process are related to the path length and the flight altitude. To minimize the flight time and assure more security, the shorter path is desirable in the trajectory planning problem. The path length is an important task in this formalism. So, the first objective function to be minimized in problem (1) is chosen as follows:

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

where (x_k, y_k, z_k), (x_1, y_1, z_1) and (x_n, y_n, z_n) are the coordinates of the waypoint k, the points S and P, respectively.

The second objective function is the flying altitude. the UAV should fly between the minimum and maximum flying heights. The objective function associated with the altitude of the path is chosen as follows:

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

where $Z_{\min}$ is the lower limit of the flying altitude in the search space, $Z_{\max}$ is the upper limit and A_{avr} is the average value of $\theta_2 = [z_2, z_3, ..., z_{n-1}]$.

The operational constraints which are considered for the path planning process are the smoothness and safety of a path. The collision avoidance with obstacles is a necessary task to solve the UAV's path planning problem with more security. 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:

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

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 ith obstacle zone, (x_i, y_i) means the center on the XOY plane and 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. To maximize the straightness of the path, the angle between two given adjacent segments is introduced. This performance constraint is illustrated by the following expression:

$$g_2(\theta)=|\varphi_{i,j}|-\varphi_{\max}\le 0 \quad ; i=1,2,\ldots,n-1; j=1,2,\ldots,m \quad (5)$$

where $\varphi_{i,j}$ is the angle between two adjacent segments, $\varphi_{\max}$ is the maximum value of the driving angle.

In conclusion, the constrained multiobjective optimization problem formulated for the UAV path planning is given as follows:

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

where $f_1(\theta)$, $f_2(\theta)$, $g_1(\theta)$ and $g_2(\theta)$ are given by equations (2), (3), (4), and (5), respectively.

To handle these operational constraints, the original optimization problem (6) is considered as an unconstrained one by the mean of penalty functions technique [17]. The augmented cost functions of the handled optimization problem are expressed as follows:

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

where $\lambda_v \in \mathbb{R}^+$ is the v^{th} penalty parameter associated to the v^{th} constraint, V is the total number of the inequality types of constraints.

III. PROPOSED MULTIOBJECTIVE MULTI-VERSE OPTIMIZER

The Multi-Verse Optimizer (MVO), originally proposed by Mirjalili et al. [18], is a recent global metaheuristic based on the physics theories of the existence of multi-verse. The interaction among different universes is ensured based on the concepts of white/black holes and wormholes. The optimization process of the MVO metaheuristic begins with a set of random solutions. At each iteration, the objects from one universe (variables) move according to their inflation rates (fitness values) to another via the white/black holes and displace within a universe or to another via a wormhole [18]. In this process, the white/black holes are used for the improvements of the exploration mechanism, while the wormholes are employed for the exploitation one.

The main updating equations in the MVO process are given as follows [18]:

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

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

To develop a multiobjective version of the MVO metaheuristic to solve the multi-criteria problems, a concept of the archive is similarly added to their research mechanism with the well-known Multiobjective Particle Swarm Optimization (MOPSO) [19]. Like MVO, the solutions of the MOMVO algorithm are enhanced using black, white, and wormholes. For selecting solutions from the archive, the 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. To remove the unsatisfactory ones, a probabilistic mechanism given by Eq. (9) is employed [19]:

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

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

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IV. DECISION MODEL

The multiobjective metaheuristics algorithms lead to a set of non-dominated solutions in the sense of Pareto. Since the path planning problem is multi-criteria, the recourse of a multi-criteria decision-making method remains essential [20, 21]. In this paper, the TOPSIS technique is used to solve such a decision-making problem.

The TOPSIS method was introduced by Hwang and Yoon in 1981. It is one of the most widely used MCDM models that consist of the following steps [20]:

Step 1: (Obtain the decision matrix). If m is the number of alternatives and n is the number of criteria, a decision matrix with m rows and n columns will be obtained as follows:

$$D=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix};\ x_{ij}\left(i=1,2,\dots m, j=1,2,\dots n\right) \quad (10)$$

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

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

Step 3: (Calculate the weighted normalized decision matrix). The matrix is obtained by multiplying the normalized decision matrix and its weights are presented as:

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

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

Step 4: (Find the positive- and negative-ideal solutions).

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

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

Step 5: (Calculate the n-dimensional Euclidean distance). The separation of each alternative from the ideal solution is given as:

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

Similarly, the separation from the negative ideal solution is given as:

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

Step 6: (Calculate the relative closeness to the ideal solution).

$$C_i=\frac{d_i^{-}}{d_i^{+}+d_i^{-}}, \qquad \mathrm{i}=1,2,\dots,\mathrm{m}. \quad (17)$$

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

The objective weight assignment of the criteria is one of the crucial problems in multi-criteria decision-making methods [22]. Determining criteria weights is the most important step of the TOPSIS technique [23]. A review of weighting methods applied in different MCDM models is presented in [24]. The standard deviation (SD) method is applied to estimate the weight factor of the different objectives [25]. This method determines the weights of criteria in terms of their standard deviations using the following equation:

$$W_j=\frac{\sigma_j}{\sum_{j=1}^{n}\sigma_j} \qquad j=1,2,\dots n \quad (18)$$

where σ_j is the standard deviation for criterion j, which is calculated using the following equation:

$$\sigma_j=\sqrt{\frac{\sum_{i=1}^{m}\left(x_{ij}-\overline{x_j}\right)^2}{m}} \qquad i=1,2,\dots m \quad (19)$$

Therefore, the TOPSIS method is applied to select the best solution from a set of the non-dominated ones of the path problem (6) taking into account the SD method, a technique of weight assignment, to estimate the criteria weights.

V. SIMULATION RESULTS AND DISCUSSIONS

For the numerical experimentations, the control parameters retained for the proposed MOMVO algorithm are given as follows: a maximum number of iterations $N_{iter}=100$, the population size $N_{pop}=100$, the minimum and maximum of wormhole existence probabilities are about 0.2 and 1, respectively. Since the resolution of the problem (6)-(7) does not give a single solution but a set of non-dominated ones, the difficulty is assimilated in the decision-making to select the best solutions. An efficient decision-making approach, i.e. the TOPSIS method, is adopted for the multiobjective path planning problem (6) resolved by the proposed MOMVO algorithm. To evaluate the performance of such a proposed MCDM method, other well-known techniques such as VIKOR [26], WSM [27], SAW [28] and EDAS [29] are considered for a comparative study. These reported multi-criteria decision-making methods are implemented and their relative performances are compared. 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.

To evaluate the performance of the proposed decision-making method for the optimization problem (6)-(7), 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.

To assess the effect of the selected MCDM methods and their chosen optimal solutions on the final result, the planned paths corresponding to the selected optimal solutions are depicted in Fig. 3. The optimal solution selected by the TOPSIS and EDAS methods as well as the WSM and SAW techniques are the same.

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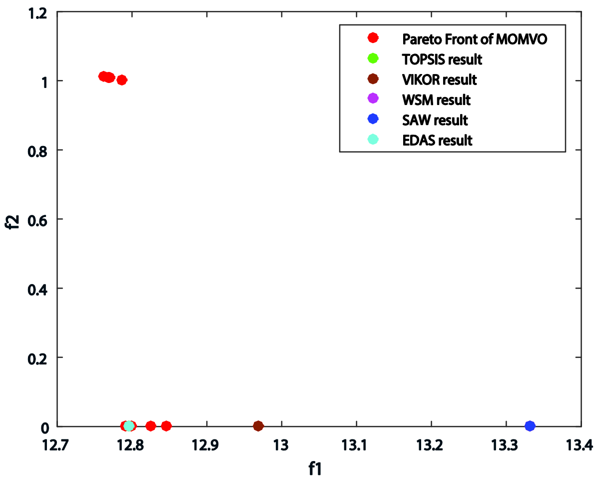

Fig 2. Optimal Pareto front obtained by MOMVO and best solution selected by different MCDM methods.

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	**12.85419**	13.04684	13.56566	13.56566	**12.85419**

Table II presents the set of non-dominated solutions given by the proposed MOMVO algorithm and the ranking patterns obtained by all MCDM techniques.

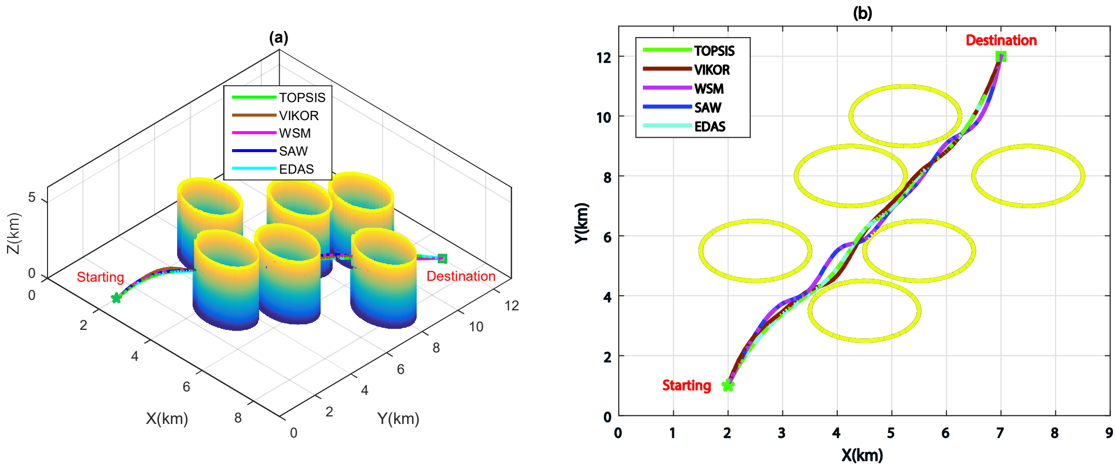

Fig. 3 Performance comparisons for UAV path planning: (a) planned path in 3D, (b) planned path in 2D

TABLE II: RANKING PATTERNS OBTAINED BY DIFFERENT MCDM TECHNIQUES

Pareto Front		**MCDM ranking methods**				
f1	f2	TOPSIS	VIKOR	WSM	SAW	EDAS
13,33199	4,2070e-06	7	12	1	1	7
12,96849	1,25516e-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	9,20491e-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

To evaluate the applicability and suitability of the five MCDM methods to solve the planning problem (6)-(7), the measure of association between their relative ranking are determined using the following measures: Kendall's coefficient of concordance [30] and Spearman's rank correlation coefficient [31].

The Kendall's coefficient of concordance (Q) value, which lies from 0 to 1 and their value of 1 results in a perfect match, is used to compare the ranking results from the five MCDM methods. Based on the data obtained in Table II, Kendall's coefficient of concordance value is calculated as $Q = 0.5815$.

The significance of the concordance coefficient is calculated as follows [32]:

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

where M is the number of experts and N is the number of criteria.

For five MCDM methods ($M = 5$), twelve non-dominated solutions ($N = 12$), and Kendall's coefficient of concordance ($Q = 0.5815$), the concordance coefficient is computed as $\chi^2 = 31.9825$. Using the table of the chi-square distribution

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with degrees of freedom $N-1=11$ and at the confidence level $\alpha = 0.05$, the critical value is equal to $\chi^2_{11,0.05} = 19.68 < \chi^2$. Hence, the null hypothesis H0 is rejected and the different MCDM methods are consistent.

The Spearman's rank correlation coefficient (r_s) is used to measure the similarity between two sets of rankings. The value of r_s lies among –1 and +1. 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 coefficient values for a set of non-dominated solutions are presented in Table III.

To test the level of significance of the correlation, we should suppose that there is no correlation between the MCDM methods. It is the null hypothesis. 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 several data pairs $N = 12$ and at the level of significance $\alpha = 0.05$ [33], the critical value is equal to $(r_s)_{0.05(1),12} = 0.503$.

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. The 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 other 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 the considered planning problem (6)-(7).

The obtained results show the effectiveness and superiority of the TOPSIS-based method to solve the path planning problem. Taking into account that the decision-making process can be influenced by the weights of criteria, it is important to pay particular attention to the selected weighting method. In this work, the SD weighting technique is used to determine the weights of criteria in the TOPSIS method. To evaluate the performance of such a proposed weighting method, other well-known techniques such as Entropy Method (EM) [34], Statistical Variance Procedure (SVP) [35], CRiteria Importance Through Inter-criteria Correlation (CRITIC) [36], and Mean Weight (MW) [23] are considered for a comparative study. Figure 4 shows the optimal Pareto front obtained by the proposed MOMVO algorithm as well as the optimal points selected by the TOPSIS technique in combination with the various weighting methods reported. To assess the impact of the criteria weighting techniques on the final result of the planning algorithm, the planned paths corresponding to the selected optimal solutions are shown in figure 5. The optimal solutions selected by the SD-TOPSIS and CRITIC-TOPSIS methods are the same. The proposed MOMVO algorithm with the TOPSIS method which is combined with various weighting methods reported to complete 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 IV. The shortest path is given by the SD-TOPSIS combination and CRITIC-TOPSIS combination.

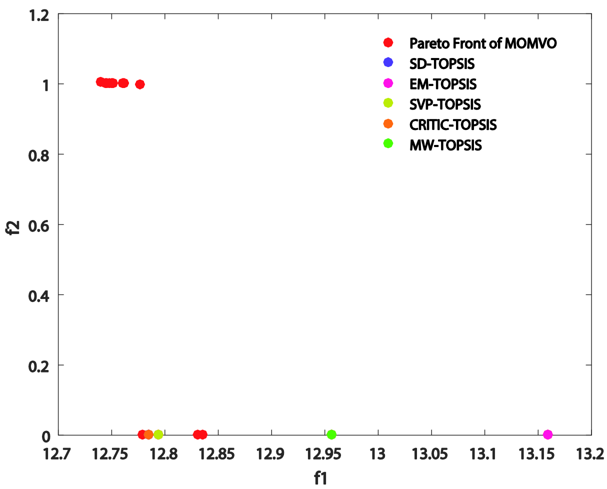

Fig 4. Optimal Pareto front obtained by MOMVO and best solution selected by TOPSIS in combination with different weighting methods.

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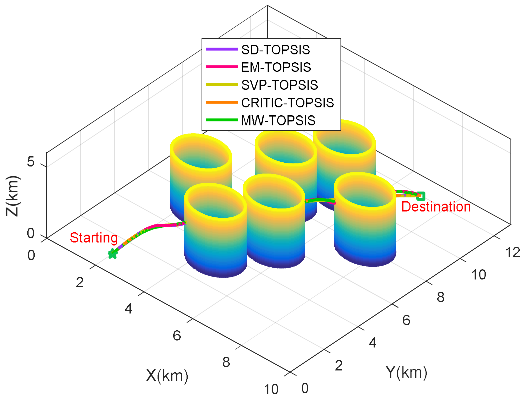

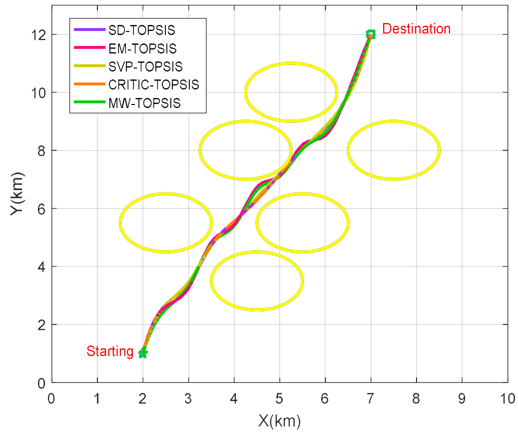

Fig. 5 Performance comparisons for UAV path planning: (a) planned path in 3D, (b) planned path in 2D

TABLE IV: PATH LENGTH OBTAINED BY TOPSIS IN COMBINATION WITH DIFFERENT WEIGHTING METHODS

Criterion	**SD-TOPSIS**	**EM-TOPSIS**	**SVP-TOPSIS**	**CRITIC-TOPSIS**	**MW-TOPSIS**
Path length	12.8288	13.3423	12.8309	12.8288	13.0577

In the following, the computed weights of the evaluation criteria obtained by different weighting methods are presented in table V.

TABLE V: ATTRIBUTE WEIGHTS OBTAINED FROM DIFFERENT WEIGHTING METHODS

Criteria	**SD**	**EM**	**SVP**	**CRITIC**	**MW**
f1	0.1743	5.81e-05	0.0426	0.3356	0.5
f2	0.8256	0.9999	0.9573	0.6643	0.5

Table VI presents the set of non-dominated solutions given by the proposed MOMVO algorithm and their corresponding ranking under various weighting approach-based TOPSIS methods.

To evaluate the correlation between each method, Spearman's rank correlation coefficients are calculated. Table IV shows the result. Based on the table of critical values of Spearman's rank correlation coefficient with several subjects $N = 16$ and at the level of significance $\alpha = 0.05$ [33], the critical value is equal to $(r_s)_{0.05(1),16} = 0.429$.

The bold values in such table designed that the hypothesis null is rejected and the correlation is significant. The highest level of significance of the correlation value of 0.9059 can be observed between the combination of SD-TOPSIS and SVP-TOPSIS. The SD-TOPSIS combination gives the shortest path in comparison with the SVP-TOPSIS combination.

The results seem to suggest that the combination SD-TOPSIS presents the most effective technique to select the optimal solution in a set of non-dominated ones obtained by the MOMVO algorithm to solve the considered planning problem (6)-(7).

TABLE VI: RANKING PATTERNS OBTAINED BY THE TOPSIS METHOD IN COMBINATION WITH DIFFERENT WEIGHTING TECHNIQUES

Pareto Front		**MCDM ranking methods**				
f1	f2	SD-TOPSIS	EM-TOPSIS	SVP-TOPSIS	CRITIC-TOPSIS	MW-TOPSIS
12.956	1.081e-05	6	2	5	6	1
13.159	5.156e-06	7	1	7	7	2
12.779	0.0008	3	7	6	2	3
12.784	0.0003	1	6	4	1	4
12.793	5.670e-05	2	5	1	3	5
12.761	1.0010	9	9	9	11	6
12.776	1.0003	8	8	8	15	7
12.744	1.0040	14	15	16	9	8
12.739	1.0041	11	16	15	8	9
12.748	1.00339	13	13	12	12	10
12.750	1.00338	16	12	13	14	11
12.760	1.0026	12	10	10	16	12
12.751	1.0027	10	11	11	13	13
12.745	1.0037	15	14	14	10	14
12.835	1.216e-05	5	3	3	5	15
12.830	1.430e-05	4	4	2	4	16

TABLE VII: SPEARMAN RANK CORRELATION COEFFICIENT VALUES OBTAINED BY DIFFERENT WEIGHTING APPROACH-BASED TOPSIS METHODS.

Methods	**SD-TOPSIS**	**EM-TOPSIS**	**SVP-TOPSIS**	**CRITIC-TOPSIS**	**MW-TOPSIS**
SD-TOPSIS	1.0000	**0.7735**	**0.9059**	**0.7882**	0.4029
EM-TOPSIS		1.0000	**0.8912**	**0.5235**	0.3588
SVP-TOPSIS			1.0000	**0.6382**	0.2176
CRITIC-TOPSIS				1.0000	0.3471
MW-TOPSIS					1.0000

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VI. Conclusion

In this paper, a proposed method based on the multi-objective multi-verse optimizer and the technique for order preference by similarity to ideal situation TOPSIS has been successfully applied to solve the multi-objective path planning problem for UAV drones in a 3D environment. Such a path planning task has been formulated as a constrained multi-objective optimization problem. The path planning process is designed to have a smooth path with a short length and an acceptable attitude avoiding all obstacles. The simulation results show the effectiveness of the proposed method. The TOPSIS-based method remains powerful compared to other reported MCDM techniques. The standard deviation (SD) method is considered to be a powerful tool for the determination of the weights of the criteria for the TOPSIS technique in comparison with other reported weighting methods. In future works, many improvements should be made. Our study will be extending to the cooperative multi-UAVs path planning problem. We will introduce also an environment with dynamic obstacles.

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