



Data-driven Controller Selection for Trajectory Control of Unmanned Ground Vehicles Through an Integrated Fuzzy Decision Framework

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ABSTRACT

Technological advances have made unmanned ground vehicles (UGVs) an integral part of modern life. Interest in UGVs has grown significantly, particularly in applications where human safety is a priority or where operations must be performed in environments inaccessible to humans. In recent years, research on UGVs has focused on key topics such as obstacle avoidance, path planning, mapping, localization, navigation, and trajectory tracking. Among these, trajectory tracking remains one of the most challenging problems and has attracted considerable attention from researchers. Furthermore, selecting an appropriate controller for trajectory tracking represents a critical decision-making problem. This study makes an important contribution to the literature, as comprehensive analyses employing multi-criteria decision-making (MCDM) methods for controller selection in UGV trajectory tracking remain scarce. In particular, systematic and comparative evaluations designed to support the controller selection process are still limited. In this context, this study is among the first to simultaneously apply fuzzy AHP and fuzzy ARTASI, two MCDM methods, to address the controller selection problem in UGV trajectory tracking. First, fuzzy AHP was employed to determine the weights of the evaluation criteria. Subsequently, six controllers were evaluated and ranked using the fuzzy ARTASI method based on seven evaluation criteria and linguistic assessments. Finally, the consistency and robustness of the obtained results were verified through a comparative analysis using the fuzzy MABAC, fuzzy TOPSIS, fuzzy VIKOR, and fuzzy MOORA methods. The findings indicate that a hybrid adaptive-sliding mode controller is the most suitable alternative for UGV trajectory tracking.

1. Introduction

Automatic control is the process of measuring one or more parameters in any system and keeping that measured parameter constant at the desired value. In daily life, automatic control is needed in many areas, from the simplest industrial process to the most complex. The fact that it is used in many areas, from the space industry to computer and communications applications, from chemical processes to robotic applications, has led researchers to focus on automatic control studies. When

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the academic studies in recent years are analysed, it is seen that many studies have been carried out on the control of unmanned vehicles [1-4]. Unmanned Ground Vehicles (UGVs) are the general name given to vehicles used on land that can move freely within a pre-designed workspace to perform their assigned task and reach desired targets. UGVs can move safely in cluttered environments, understand speech, recognise real objects, position themselves, plan their paths, navigate and generally think on their own using programmable computers mounted on them [5].

UGVs can fulfil a variety of tasks thanks to their diverse usage areas and design structures. Examining the academic studies conducted in recent years reveals that many have focused on topics such as path planning, navigation, obstacle avoidance, localisation, control architectures, mapping and trajectory tracking control [5,6]. The variety of usage areas and designs of UGVs has resulted in a range of encountered problems. Despite being one of the most studied topics, the trajectory tracking control problem remains relevant [4,7-11]. The main objective of trajectory tracking control is to ensure that the UGV follows a predetermined reference trajectory with minimum error. However, the fact that UGVs have a nonlinear system structure and contain uncertainties makes trajectory tracking control of UGVs difficult [12]. Numerous control methods such as PID control, backstepping control, fuzzy control, intelligent control, sliding mode control and adaptive control are frequently preferred to realise the trajectory control of UGVs [13-18].

PID controllers, which have been widely used in industrial processes in recent years, are simple in design and reliable. They do not require a precise dynamic mathematical model of the system they control and their parameters are easy to tune [12]. However, fixed-gain PID controllers are of limited use in UGVs where system behaviour is constantly changing, as they do not provide the desired tracking performance [19]. Backstepping control is a preferred method for trajectory tracking control in UGVs, particularly for nonlinear systems. It is based on the Lyapunov theorem, which is used for stability analysis of systems. It effectively handles system constraints and is highly robust to uncertainties and disturbances [20,21]. However, its use is limited in UGVs with constraints because its design and implementation are very complex and computationally intensive, and its performance is strictly dependent on the correct parameter values. Fuzzy control has been preferred for the control of UGVs because it is a control technique that allows the system to operate with the determined rule tables in cases where the system model is unknown, is robust to uncertainties, and can easily adapt to changes in the system [22,23]. However, the lack of a mathematical model, complex rules and a large number of parameters limit the use of the controller [24]. In addition, the subjective selection of membership functions and the lengthy and costly operations can lead to inconsistencies in the performance of the controller, thus limiting the use of UGVs in trajectory tracking control. Intelligent control is a control technique that aims to solve control problems based on the functioning of biological systems, does not require a mathematical model of the systems, can work without knowing everything about the system dynamics and conditions, and can be easily applied to complex systems [25]. However, its use is limited because it requires a lot of processing in terms of application and training, and the training data is not predefined in UGVs to be used for practical applications. Adaptive control method has been frequently preferred in recent years to perform trajectory tracking control of UGVs since it can automatically adjust its control parameters against changes in the system, structural disturbances, uncertainties and external disturbances and can quickly adapt to environmental changes [26-28]. It is also able to estimate and compensate the model uncertainties of the UGV in real-time applications where precise modelling is difficult. Sliding mode control method is often preferred to perform trajectory tracking control of UGVs due to its advantages such as easy design, high accuracy, robustness to uncertainties in the system and external disturbances, and insensitivity to model uncertainties [29-32]. However, its biggest disadvantage is

that it causes chattering in the system to which it is applied, but this chattering effect can be reduced or eliminated in various ways [33,34].

The above-mentioned controllers can perform successfully under certain conditions. Therefore, before selecting a controller, the purpose and conditions under which the UGV will be used should be clearly determined. Criteria such as applicability to nonlinear systems, ease of design, the need for a system model, robustness, fast response capability, applicability to real-time systems, and the ability to update controller parameters should be taken into consideration when selecting a controller. In real-time applications, since the system parameters are not known precisely and the system states are constantly changing, it is insufficient to achieve the desired tracking performance by using only a single controller for trajectory control of UGVs. For this reason, hybrid controller structures are designed by combining controllers in pairs or trios to utilize the significant advantages of these controllers [35-37]. However, which of these designed controllers will be hybridized with each other is not based on a specific technique. When the academic studies in the literature are examined, controller designs have been realized by utilizing the studies conducted in previous years or by testing more than one controller on criteria that measure control performances (such as IAE, ISE, ITAE) and comparing their results. However, it has been observed that the preferences of decision makers have not been analysed in detail in this process. In this study, the controller selection process is addressed systematically and quantitatively with a multi-criteria decision making (MCDM) method based on the evaluations of decision makers within the framework of certain criteria. In this way, the study makes a methodological and practical contribution to the literature.

2. Material and Method

2.1. An Integrated Fuzzy AHP and ARTASI Multi-Criteria Framework

This chapter presents a multi-criteria decision-making framework that integrates the Analytic Hierarchy Process (AHP) and ARTASI methods for complex decision-making problems in engineering systems, especially the selection of the optimal controller for UGVs. While the AHP method is used to determine the criteria weights, the ARTASI method evaluates and ranks the performance of the alternatives based on these weights. This integration improves the accuracy of the decision-making process and provides an effective solution to similar complex evaluation problems such as UGV trajectory tracking control. Figure 1 shows the methodological framework of fuzzy AHP-ARTASI.

a) Fuzzy AHP

AHP, one of the multi-criteria decision-making approaches, was first proposed by Saaty. AHP is a method that facilitates the hierarchical solution of multi-attribute, multilateral and multi-period structural problems. Although its aim is to evaluate expert knowledge, the classical AHP method cannot respond to the uncertainty in human thinking. Therefore, fuzzy AHP is recommended for the solution of such problems [38]. Fuzzy AHP (F-AHP) approach is a very effective method for decision makers as it allows making judgements with values in certain ranges instead of working with exact values.

Since decision makers use natural linguistic emphases as well as exact numbers when they evaluate criteria and alternatives, the F-AHP method impressively resembles human thoughts and perceptions. For this reason, it has been systematically used by many different researchers on different topics. For example, the problem of industrial engineering sector choosing [39], warehouse location selection [40], supplier selection [41], determination of investment priority sectors [42] and strategic alliance partner selection [43] and so on.

The steps of the F-AHP method used in determining the weights of the criteria are as follows:



Fig. 1. Methodology Framework of Fuzzy AHP -ARTASI Methods

Step 1: Pairwise comparison matrices are created according to the opinions of decision makers (DMs). (Eq. (1))

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \dots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \dots & 1 \end{bmatrix}_{n \times n} = \begin{bmatrix} 1 & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \\ 1/\tilde{a}_{12} & 1 & \dots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\tilde{a}_{1n} & 1/\tilde{a}_{2n} & \dots & 1 \end{bmatrix}_{n \times n} \quad (1)$$

$$\tilde{a}_{ij} = \begin{cases} \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9} & \text{criterion } i \text{ is relatively more important than criterion } j \\ 1 & i = j \\ \tilde{1}^{-1}, \tilde{3}^{-1}, \tilde{5}^{-1}, \tilde{7}^{-1}, \tilde{9}^{-1} & \text{criterion } i \text{ is relatively less important than criterion } j \end{cases} \quad (2)$$

In Eq. (2), α_{ij} is fuzzy comparison value of dimension i to criterion j , decision-makers use the scale in Table 1 to evaluate the criteria.

Table 1

Triangular fuzzy number (TFN) type correspondences of linguistic variables used in the evaluation

Linguistic Variable	Triangular Fuzzy Scale	Triangular Fuzzy Reciprocity Scale
Equal importance	(1, 1, 1)	(1/1, 1/1, 1/1)
Medium importance	(1, 3, 5)	(1/5, 1/3, 1/1)
Strong importance	(3, 5, 7)	(1/7, 1/5, 1/3)
Very strong importance	(5, 7, 9)	(1/9, 1/7, 1/5)
Absolute importance	(7, 9, 9)	(1/9, 1/9, 1/7)

Step 2: Fuzzy geometric means and fuzzy weights of each criterion are calculated using the geometric mean technique proposed by Buckley [44], as given in Eq. (3) and Eq. (4), during the construction of the pairwise comparison matrix [44].

$$\tilde{r}_i = (\tilde{\alpha}_{i1} \otimes \dots \otimes \tilde{\alpha}_{ij} \otimes \dots \otimes \tilde{\alpha}_{in})^{1/n} \tag{3}$$

$$\tilde{\omega}_i = \tilde{r}_i [\tilde{r}_1 \oplus \dots \oplus \tilde{r}_i \oplus \dots \oplus \tilde{r}_n]^{-1} \tag{4}$$

where \tilde{r}_i is a geometric mean of fuzzy comparison value of criterion i to each criterion, $\tilde{\omega}_i$ is the fuzzy weight of the i^{th} criterion, can be indicated by a TFN, $\tilde{\omega}_i = (l\omega_i, m\omega_i, u\omega_i)$. The $l\omega_i$, $m\omega_i$ and $u\omega_i$ stand for the lower, middle, and upper values of the fuzzy weight of the i^{th} dimension respectively for a triangular fuzzy number.

Step 3: In the last step, the fuzzy criterion weights obtained in the previous step are defuzzified, and the Best Non-Fuzzy Performance (BNP) values are calculated. For ease of calculation, the Center of Area (COA) method was used in the calculation process by using Eq. (5) [45]:

$$BNP_{\omega_i} = [(u\omega_i - l\omega_i) \oplus (m\omega_i - l\omega_i)]/3 \oplus l\omega_i \tag{5}$$

Crisp weights for each criterion were obtained using the above formula.

b) Fuzzy ARTASI

The ARTASI (Alternative ranking technique based on adaptive standardized intervals) technique was developed by Pamucar *et al.*, [46]. This method allows alternatives to be ranked according to their performance under multiple criteria. The method uses a standardized intervals approach to make the comparison between alternatives more consistent and robust, which is particularly advantageous when there are conflicting criteria or criteria with different scales. One of the important features of ARTASI is that it can incorporate both benefit-type (maximizing) and cost-type (minimizing) criteria into the evaluation process.

To better address the uncertainty and subjectivity in expert evaluations, a fuzzified version of the method, fuzzy ARTASI, was developed. With this approach, imprecise evaluations of alternatives are represented by fuzzy numbers, thus modelling the uncertainty in decision makers' preferences in a more flexible and realistic way. Thanks to the integration of fuzzy logic, this method enables more effective management of uncertainty, especially in areas such as engineering, transportation and risk assessment. The steps of fuzzy ARTASI are as follows:

Step 1: Fuzzy decision matrices are constructed for each decision-maker based on the evaluation of alternatives with respect to the criteria, where the decision-makers use the scale provided in Table 2.

$$[\tilde{B}_{ijk}]_{m \times n} = \begin{bmatrix} \check{\phi}_{11k} & \dots & \check{\phi}_{1nk} \\ \vdots & \ddots & \vdots \\ \phi_{m1k} & \dots & \phi_{mnk} \end{bmatrix} \tag{6}$$

In Eq. (6), $\check{\phi}_{11k} = \check{F}(l_{ijk}, m, u_{ijk})$ (with $i=1,2, \dots, m; j=1,2, \dots, n$) denotes the assessment of the i^{th} alternative based on the j^{th} criterion by decision maker k .

Table 2

Linguistic variables used in the evaluation of alternatives	
Linguistic Variable	Triangular Fuzzy Numbers
Very Weak	(0, 0, 1)
Weak	(0, 1, 3)
Medium Weak	(1, 3, 5)
Middle	(3, 5, 7)
Middle Good	(5, 7, 9)
Good	(7, 9, 10)
Very Good	(9, 10, 10)

Step 2: Calculate the fuzzy aggregated decision matrix $[\check{B}_{ijk}]_{m \times n}$ employing the geometric mean method as given in Eq. (3) and obtain the combined fuzzy decision matrix $\check{D}_{ij} = \check{F}(\check{L}_{ij}, \check{M}_{ij}, \check{U}_{ij})$

Step 3: The combined fuzzy decision matrix \check{D}_{ij} is normalized using Eq. (7) and (8) to standardize the fuzzy values, resulting in the normalized fuzzy decision matrix \tilde{N}_{ij} . Let the set B denote the benefit criteria and the set C denote the cost criteria; the normalized fuzzy decision matrix is then calculated accordingly.

$$\tilde{N}_{ij} = \frac{a_{ij}}{\max_i c_{ij}}, \frac{b_{ij}}{\max_i c_{ij}}, \frac{c_{ij}}{\max_i c_{ij}}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \text{ for } j \in B \quad (7)$$

$$\tilde{N}_{ij} = \frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}, i = 1, 2, \dots, m; j = 1, 2, \dots, n \text{ for } j \in C \quad (8)$$

Step 4: Subsequently, the normalized fuzzy decision matrix \check{D}_{ij} is defuzzified; that is, the defuzzified decision matrix ($\mathcal{D} = [\mathcal{D}_{ij}]_{m \times n}$) is estimated using Eq. (9).

$$\mathcal{D}_{ij} = \frac{(4\check{M}_{ij} + \check{L}_{ij} + \check{U}_{ij})}{6} \quad (9)$$

Step 5: Define absolute maximum ($\mathcal{D}^{\max} = [\mathcal{D}_j^{\max}]_n$) and minimum ($\mathcal{D}^{\min} = [\mathcal{D}_j^{\min}]_n$) and values of the defuzzified decision matrix $[\mathcal{D}_{ij}]_{m \times n}$ in j criterion using Eqs. (10) and (11), respectively.

$$\mathcal{D}_j^{\max} = \max_{1 \leq i \leq m} (\mathcal{D}_{ij}) + \left\{ \max_{1 \leq i \leq m} (\mathcal{D}_{ij}) \right\}^{1/m} \quad (10)$$

$$\mathcal{D}_j^{\min} = \min_{1 \leq i \leq m} (\mathcal{D}_{ij}) + \left\{ \min_{1 \leq i \leq m} (\mathcal{D}_{ij}) \right\}^{1/m} \quad (11)$$

Step 6: In order to take into account the two different types of criteria (cost and benefit) used in the evaluation matrix components, the criteria values need to be transformed into a standardized base or range. Unlike traditional normalization methods that use the traditional interval [0,1], this approach transforms the criteria values into a standard interval determined by the subjective preferences of the decision makers. When standardizing the defuzzified evaluation matrix $[\mathcal{D}_{ij}]_{m \times n}$ the components are transformed into a randomly chosen criteria range $[\Psi^u, \Psi^l]$, where (Ψ^l) represents the lower boundary of the range and (Ψ^u) represents the upper boundary.

Step 7: The matrix $[\phi_{ij}]_{m \times n}$ is created by standardization of the defuzzified decision matrix. Furthermore, the standardized interval $[\Psi^l, \Psi^u]$ is taken as [1,100] [46]. The initial decision matrix $\Delta = [\phi_{ij}]_{m \times n}$ undergoes standardization in the first step, where all its elements are processed as follows (in Eq. (12):

$$\wp_{ij} = \frac{\Psi^{(u)} - \Psi^{(l)}}{\mathcal{D}_j^{max} - \mathcal{D}_j^{min}} \mathcal{D}_{ij} + \frac{\mathcal{D}_j^{max * \Psi^{(l)}} - \mathcal{D}_j^{min * \Psi^{(u)}}}{\mathcal{D}_j^{max} - \mathcal{D}_j^{min}} \quad (12)$$

In order to transform the values of the cost-type criteria in the matrix $[\wp_{ij}]_{m \times n}$, the inverse sorting procedure given in Eq. (13) is applied to obtain the final standardized matrix $[\mu_{ij}]_{m \times n}$.

$$[\mu_{ij}]_{m \times n} = \begin{pmatrix} (\mu_{ij}) = \left(-\wp_{ij} + \max_{1 \leq i \leq m} \wp_{ij}\right); \text{if } j \in \text{cost criteria} \\ (\mu_{ij}) = (\wp_{ij}); \text{if } j \in \text{benefit criteria} \end{pmatrix} \quad (13)$$

Step 8: The utility levels of the alternatives for the ideal (Δ_{ij}^+) and non-ideal (Δ_{ij}^-) values are calculated using Eq. (14) and Eq. (15) respectively.

$$\Delta_{ij}^+ = \frac{\mu_{ij}}{\max_{1 \leq i \leq m} \mu_{ij}} \times \omega_j \times \Psi^u \quad (14)$$

$$\Delta_{ij}^- = -\Delta_{ij} + \max_{1 \leq i \leq m} \Delta_{ij} + \min_{1 \leq i \leq m} \Delta_{ij} \quad (15)$$

Where Δ_{ij} is level of usefulness. Δ_{ij} is computed using Eq. (16)

$$\Delta_{ij} = \frac{\min_{1 \leq i \leq m} (\mu_{ij})}{\mu_{ij}} \times \omega_j \times \Psi^u \quad (16)$$

Where $\Psi^u = 100$ and ω_j are criterion weights.

Step 9: The total (integrated) utility levels of the alternatives for the ideal (τ_i^+) and non-ideal (τ_i^-) values are calculated using Eq. (17) and Eq. (18), respectively.

$$\tau_i^+ = \sum_{j=1}^n \Delta_{ij}^+ \quad (17)$$

$$\tau_i^- = \sum_{j=1}^n \Delta_{ij}^- \quad (18)$$

Step 10: The final utility functions (Γ_i) are calculated using Eq. (19) and the alternatives are ranked in descending order.

$$\Gamma_i = (\tau_i^+ + \tau_i^-) \left\{ \beta \cdot f(\tau_i^+)^\mathfrak{N} + (1 - \beta) \cdot f(\tau_i^-)^\mathfrak{N} \right\}^{\frac{1}{\mathfrak{N}}}; \beta \in [0, 1]; \mathfrak{N} \in [0, +\infty] \quad (19)$$

Where $f(\tau_i^+) = \frac{\tau_i^+}{\tau_i^+ + \tau_i^-}$ and $f(\tau_i^-) = \frac{\tau_i^-}{\tau_i^+ + \tau_i^-}$ represented the additive functions. β specifies the effect of the aggregated utility levels of the alternatives (τ_i^+ and τ_i^-) in the ultimate choice, \mathfrak{N} indicates the stabilization parameter of Γ_i .

3. Proposed Fuzzy -AHP and Fuzzy-ARTASI Controller Selection model

In real life, automatic control is needed in many areas. Therefore, deciding which controller to use is an important decision problem. In this study, F-AHP and F-ARTASI methods, which are among to the multi-criteria decision-making techniques, are applied to the controller selection problem. First, six alternative controllers (PID control, backstepping control, fuzzy control, intelligent control, sliding mode control and adaptive control) and seven criteria (applicability to nonlinear systems, ease of design, no need for system model, robustness, fast response, easy application to real-time systems and ability to update controller parameters) were evaluated by decision makers. The hierarchical structure of the controller selection problem is shown in Figure 2.

4. Discussion and Results

In the first stage of the study, the F-AHP technique was used to determine the weights of the criteria for controller selection. The responses of five decision makers, who are experts in their fields and have academic studies in this field, regarding the selection criteria were evaluated using the triangular fuzzy numbers in Table 1. Fuzzy decision matrices were created separately for each decision maker using Eq. (1) and (2), and then these matrices were combined using Eq. (3) to obtain the criteria combined binary fuzzy comparison matrix. The relevant matrix is presented in Table 3.

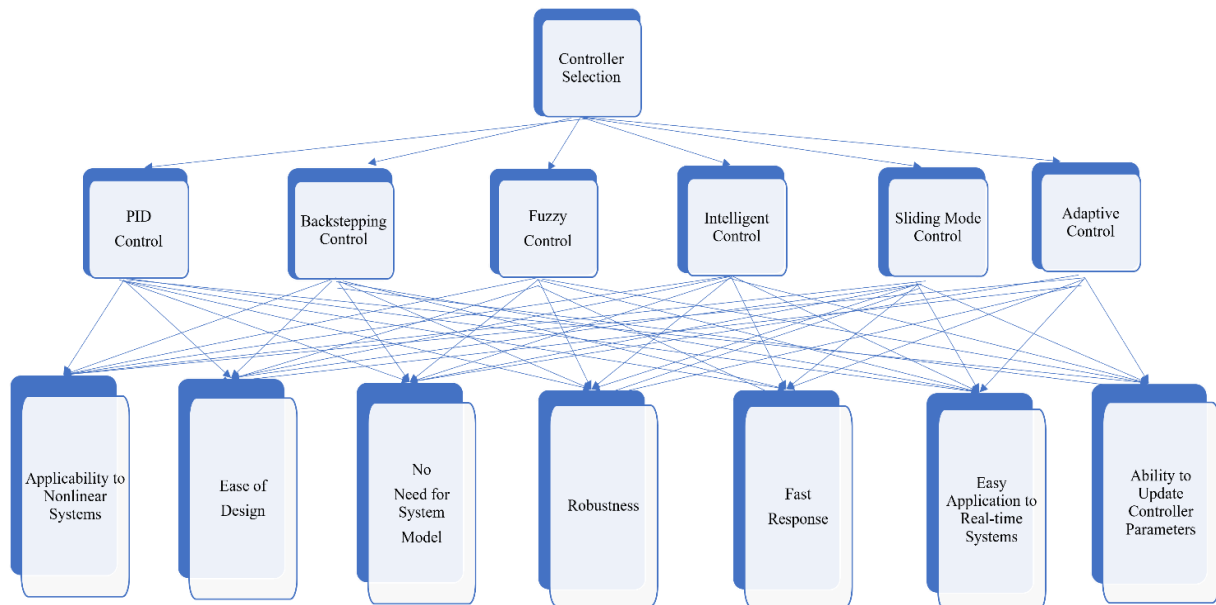


Fig. 2. Hierarchical structure of controller selection

Table 3

Criteria combined binary fuzzy comparison matrix

	Applicability to Nonlinear Systems	Ease of Design	No Need for System Model	Robustness
Applicability to Nonlinear Systems	(1 1 1)	(1 1 1)	(1 1 1)	(3.557 5.59 7.61)
Ease of Design	(1 1 1)	(1 1 1)	(1.913 3 3.56)	(1 2.08 2.92)
No Need for System Model	(1 1 1)	(0.281 0.333 0.52)	(1 1 1)	(2.08 2.92 3.66)
Robustness	(0.131 0.18 0.28)	(0.342 0.481 1)	(0.273 0.34 0.48)	(1 1 1)
Fast Response	(0.131 0.18 0.28)	(0.16 0.237 0.48)	(0.147 0.21 0.41)	(0.231 0.25 0.31)
Easy Application to Real-Time Systems	(0.121 0.15 0.21)	(0.342 0.481 1)	(0.585 0.69 1)	(0.481 0.52 0.58)
Ability to Update Controller Parameters	(0.251 0.28 0.36)	(0.179 0.281 0.69)	(0.481 0.52 0.58)	(0.231 0.27 0.34)
	Robustness	Fast Response	Easy Application to Real-Time Systems	
Applicability to Nonlinear Systems	(3.557 5.59 7.61)	(3.557 5.59 7.61)	(4.72 6.8 8.277)	
Ease of Design	(1 2.08 2.92)	(2.08 4.22 6.26)	(1 2.08 2.924)	
No Need for System Model	(2.08 2.92 3.66)	(2.466 4.72 6.8)	(1 1.44 1.71)	
Robustness	(1 1 1)	(3.271 3.98 4.33)	(1.71 1.91 2.08)	
Fast Response	(0.231 0.25 0.31)	(1 1 1)	(1.91 2.08 2.08)	
Easy Application to Real-Time Systems	(0.481 0.52 0.58)	(0.481 0.48 0.52)	(1 1 1)	

Fuzzy weights are obtained for each criterion group using Eq. (4). The fuzzy weights of the criteria are given in Table 4.

Subsequently, the defuzzified weights were calculated using Eq. (5), as shown below:

$$\omega_1 = 0,3131, \omega_2 = 0,2594, \omega_3 = 0,1786, \omega_4 = 0,1265, \omega_5 = 0,0756, \omega_6 = 0,0861, \omega_7 = 0,0502.$$

Table 4
 Fuzzy weight matrix of criteria

Criteria / Fuzzy Weight	$l\omega_i$	$m\omega_i$	$u\omega_i$
Applicability to Nonlinear Systems	0.191	0.3	0.45
Ease of Design	0.118	0.24	0.42
No Need for System Model	0.105	0.17	0.27
Robustness	0.073	0.11	0.19
Fast Response	0.039	0.07	0.12
Easy Application to Real-Time Systems	0.048	0.08	0.13
Ability to Update Controller Parameters	0.026	0.04	0.08

In the second part of the study, each decision maker evaluated the six controller alternatives by considering seven criteria using the linguistic expressions in Table 2. The fuzzy decision matrices generated from the evaluations of the decision makers were first aggregated using the geometric mean method as given in Eq. (3). The combined decision matrix was then normalized using Eq. (7) and (8). The normalised fuzzy decision matrix is presented in Table 5. The normalized fuzzy decision matrix was defuzzified using Eq. (9) to derive the crisp decision matrix, as shown in Table 6.

Table 5
 Normalised fuzzy decision matrix

	Applicability to Nonlinear Systems	Ease of Design	No Need for System Model	Robustness
PID Control	(0 0 0.1)	(1 1 1)	(1 1 1)	(0 0 0.208)
Backstepping Control	(0.481 0.629 0.788)	(0.160 0.356 0.559)	(0 0 0.144)	(0 0.412 0.646)
Fuzzy Control	(0.638 0.766 0.888)	(0 0 0.311)	(0.481 0.629 0.788)	(0.442 0.646 0.794)
Intelligent Control	(1 1 1)	(0 0.144 0.356)	(0.231 0.422 0.626)	(0.637 0.766 0.888)
Sliding Mode Control	(0.693 0.794 0.888)	(0.333 0.531 0.705)	(0 0.464 0.669)	(0 0.481 0.669)
Adaptive Control	(1 1 1)	(0 0 0.276)	(0 0.464 0.669)	(1 1 1)
	Fast Response	Easy Application to Real-Time Systems	Controller Parameters	
PID Control	(0.638 0.766 0.888)	(0.251 0.437 0.626)	(0 0 0.1)	
Backstepping Control	(0 0.448 0.669)	(0.756 0.857 0.965)	(0 0 0.311)	
Fuzzy Control	(0 0.448 0.669)	(0.756 0.857 0.965)	(0.778 0.9 1)	
Intelligent Control	(0 0.464 0.669)	(0 0.448 0.669)	(0.586 0.740 0.888)	
Sliding Mode Control	(1 1 1)	(0.693 0.794 0.888)	(0 0 0.191)	
Adaptive Control	(0.753 0.822 0.888)	(1 1 1)	(1 1 1)	

The absolute maximum and minimum values of the defuzzified decision matrix were determined using Eq. (10) and (11), and are presented in Table 7. The defuzzified (crisp) decision matrix was used in Eq. (12) to obtain the primary level standardized decision matrix, which is presented in Table 8. Since all criteria are benefit criteria, the final standardized matrix obtained using Eq. (13) is considered the final standardized decision matrix. The utility degrees of the alternatives with respect to the ideal and anti-ideal values were calculated using Eq. (14), (15) and (16), based on the criteria weights obtained by the fuzzy AHP method, and are presented in Tables 9 and 10, respectively.

Table 6
 The crisp decision matrix

	Applicability to Nonlinear Systems	Ease of Design	No Need for System Model	Robustness
PID Control	0.017	1	1	0.0347
Backstepping Control	0.632	0.357	0.024	0.382
Fuzzy Control	0.765	0.0518	0.631	0.637
Intelligent Control	1	0.155	0.424	0.765
Sliding Mode Control	0.793	0.527	0.421	0.432
Adaptive Control	1	0.046	0.421	1
	Fast Response	Easy Application to Real-Time Systems	Controller Parameters	
PID Control	0.765	0.437	0.017	
Backstepping Control	0.410	0.858	0.052	
Fuzzy Control	0.410	0.858	0.896	
Intelligent Control	0.421	0.410	0.739	
Sliding Mode Control	1	0.793	0.032	
Adaptive Control	0.822	1	1	

Table 7
 The absolute maximum and minimum values matrices

\mathcal{D}	Applicability to Nonlinear Systems	Ease of Design	No Need for System Model	Robustness
\mathcal{D}_j^{max}	2	2	2	2
\mathcal{D}_j^{min}	-0.489	-0.553	-0.513	-0.536
\mathcal{D}	Fast Response	Easy Application to Real-Time Systems	Controller Parameters	
\mathcal{D}_j^{max}	2	2	2	
\mathcal{D}_j^{min}	-0.452	-0.452	-0.489	

Table 8
 The primary level standardized decision matrix

	Applicability to Nonlinear Systems	Ease of Design	No Need for System Model	Robustness
PID Control	21.105	61.215	60.608	23.288
Backstepping Control	45.562	36.279	22.162	36.864
Fuzzy Control	50.878	24.439	46.091	46.793
Intelligent Control	60.221	28.459	37.916	51.800
Sliding Mode Control	51.974	42.879	37.799	38.800
Adaptive Control	60.221	24.214	37.799	60.968
	Fast Response	Easy Application to Real-Time Systems	Controller Parameters	
PID Control	50.136	36.901	21.105	
Backstepping Control	35.809	53.903	22.502	
Fuzzy Control	35.809	53.903	56.096	
Intelligent Control	36.240	35.809	49.837	
Sliding Mode Control	59.620	51.248	21.710	
Adaptive Control	52.420	59.620	60.221	

Table 9
 The degree of utility of the ideal matrix

	Applicability to Nonlinear Systems	Ease of Design	No Need for System Model	Robustness
PID Control	10.687	25.192	17.203	4.554
Backstepping Control	23.071	14.93	6.290	7.208
Fuzzy Control	25.763	10.057	13.082	9.150
Intelligent Control	30.494	11.712	10.762	10.129
Sliding Mode Control	26.318	17.646	10.729	7.587
Adaptive Control	30.494	9.965	10.729	11.922
	Fast Response	Easy Application to Real-Time Systems	Controller Parameters	
PID Control	5.922	5.007	1.588	
Backstepping Control	4.229	7.314	1.693	
Fuzzy Control	4.229	7.314	4.222	
Intelligent Control	4.281	4.859	3.751	
Sliding Mode Control	7.042	6.954	1.634	
Adaptive Control	6.192	8.090	4.532	

Table 10
 The degree of utility of the non-ideal matrix

	Applicability to Nonlinear Systems	Ease of Design	No Need for System Model	Robustness
PID Control	10.687	25.192	17.203	4.554
Backstepping Control	27.056	18.34252	6.290	8.944
Fuzzy Control	28.532	10.197	15.222	10.542
Intelligent Control	30.494	13.722	13.438	11.116
Sliding Mode Control	28.798	20.931	13.407	9.320
Adaptive Control	30.494	9.965	13.407	11.922
	Fast Response	Easy Application to Real-Time Systems	Controller Parameters	
PID Control	6.242	5.098	1.588	
Backstepping Control	4.230	7.575	1.867	
Fuzzy Control	4.230	7.575	4.415	
Intelligent Control	4.313	4.859	4.201	
Sliding Mode Control	7.042	7.296	1.715	
Adaptive Control	6.461	8.090	4.532	

The total (integrated) utility degrees of the alternatives with respect to the ideal and anti-ideal values were calculated using Eq. (17) and (18), respectively, and are presented in Figure 3. The final utility functions are calculated using Eq. (19), and the alternatives are ranked in descending order. The final utility functions and the ranking of alternatives are presented in Table 11.

According to Table 11, the best alternative is sliding mode control, and the other alternatives are adaptive control, intelligent control, fuzzy control, back stepping control and PID control respectively. Sliding mode control's top ranking clearly reflects its exceptional robustness and ability to maintain high performance even under system uncertainties and external disturbances. Its strong fault tolerance and fast dynamic response make it especially suitable for managing complex, nonlinear systems. Compared to other control methods, it consistently offers superior stability and reliability,

establishing itself as the most effective approach in this analysis. These results demonstrate the consistency and validity of the study.

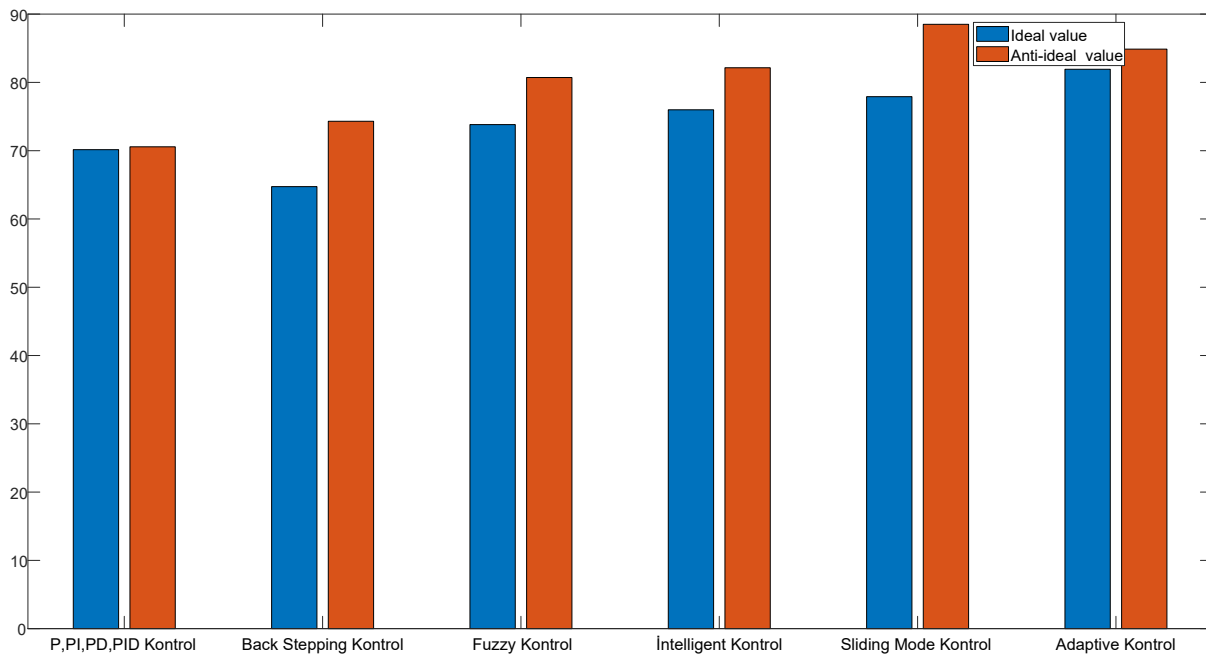


Fig. 3. The aggregate level of utility of the alternatives for the ideal value and the nonideal value matrix

Table 11

The final utility functions matrix and the ranking of alternatives

Alternatives	Γ_i	Ranking
PID Control	70.48	6
Backstepping Control	72.39	5
Fuzzy Control	79.33	4
Intelligent Control	80.91	3
Sliding Mode Control	86.36	1
Adaptive Control	84.28	2

4.1. Sensitivity Analysis

In the calculation of the final utility functions, the parameter β in Equation (19) varies within the range [0,1]. In this section, the final utility functions were recalculated for β values of 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and a sensitivity analysis was conducted accordingly.

The radar plot presented in Figure 4 shows how the different control strategies differ in the final utility values according to the variation of the parameter β between 0.1 and 0.9. In this sensitivity analysis, the alternatives located closest to the center perform the best. According to the results of the analysis, when the value of β is between 0.1 and 0.4, the sliding mode control strategy ranks first by reaching the lowest utility value among all alternatives. However, when the value of β increases between 0.5 and above 0.5, the adaptive control strategy takes the lead and performs the best for all values from 0.5 to 0.9. This shows that for decision makers, the preferred alternative may change depending on the uncertainty level of the system.

On the other hand, the “P, PI, PD, PID control” and “back stepping control” strategies remained in the outermost rings for all β values and had the highest utility values, which indicates that they are at the bottom of the ranking. The “fuzzy” and “intelligent” control strategies showed a moderate performance and largely maintained their positions in the ranking. These findings clearly reveal the sensitivity of the control strategies to changes in the β parameter and show that sliding mode and

adaptive control strategies in particular stand out at certain levels of uncertainty. These differences in the rankings emphasize the flexibility of the decision model and the need for dynamic evaluation in the context of the β parameter.

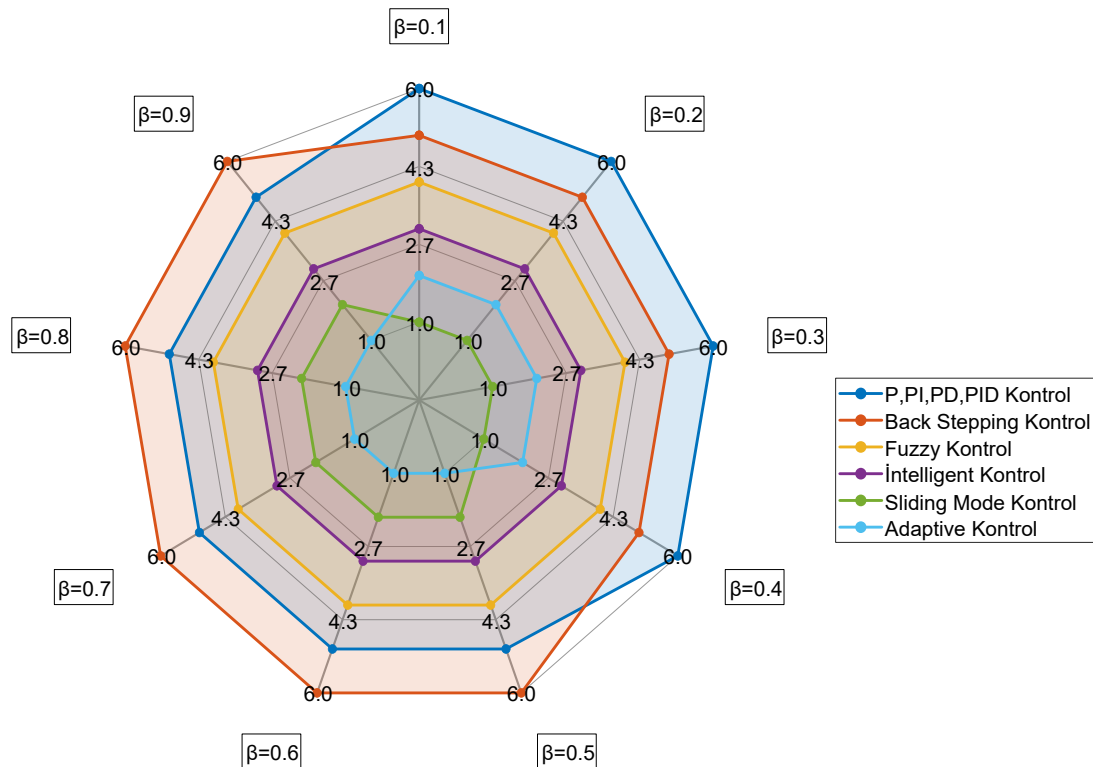


Fig. 4. Sensitivity of Alternative Rankings to Changes in the β values

In the following section, the analysis of the sensitivity of the fuzzy ARTASI model during the variation of the parameter Ψ^u used in equation (12) is presented. Initial results from Table 11 were obtained for parameter values $\Psi^u=100$. Since Ψ^u can have values from the interval $0 < \Psi^l < +\infty$, in the following part the influence of the parameter change in the interval $0 < \Psi^l < +\infty$ on the changes in the ranks of the alternatives was analyzed, Figure 5.

Figure 5 presents ten scenarios during which the parameter change was simulated. In the first scenario, the value $\psi^u=10$ was adopted, while in each subsequent scenario it was increased by $\psi^u (S_n) = \psi^u (S_n-1)+10$, where S_n represents the nth scenario. The results from Figure 5 show that the parameter ψ^u affects the changes in the values of the score functions. However, the changes in score functions from Figure 5 do not indicate changes in the ranks of the alternatives, but confirm that the initial solution shown in Table 11 is stable. The results from Figure 5 confirm that the initial solution is credible and that the Sliding Mode Control alternative represents the dominant solution from the considered set of alternatives.

4.2. Comparative Analysis with other MCDM Techniques

In this study, the F-ARTASI method is employed to address the alternative controller selection problem, offering a structured approach to evaluate multiple control strategies under fuzzy conditions. To validate the robustness, reliability, and consistency of the obtained results, a comparative analysis is conducted in this section using four well-established fuzzy multi-criteria decision-making (FMCDM) methods: F-MABAC, F-TOPSIS, F-VIKOR, and F-MOORA. The ranking results obtained by each method are presented in Figure 6. By comparing the rankings and

performance scores derived from these methods, the aim is to assess the accuracy of the proposed F-ARTASI-based evaluation and to identify the degree of agreement across different decision-making frameworks. This multi-method approach strengthens the credibility of the findings and provides deeper insight into the stability of the selected optimal controller under varying evaluation techniques.

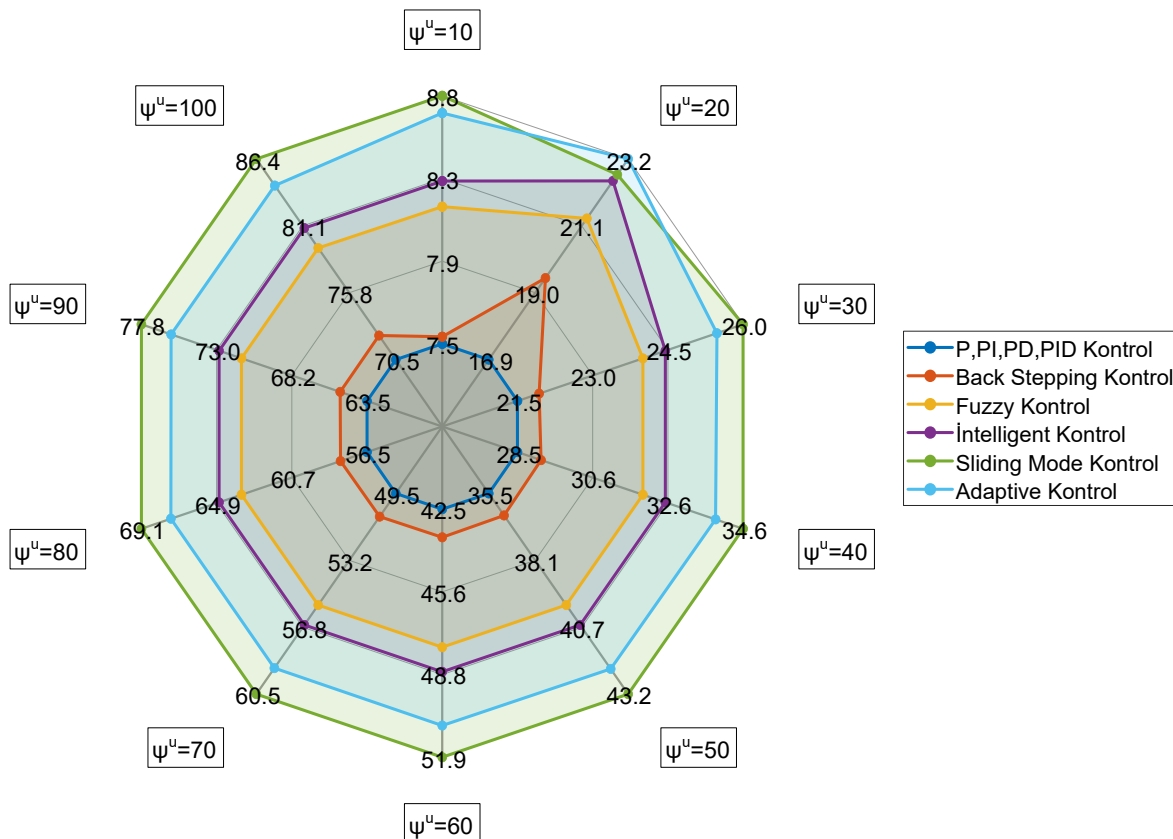


Fig. 5. Sensitivity of Alternative Rankings to Changes in $1 < \Psi^l < 100$ values

In the Radar graph in Figure 6, the performance values of six different control strategies obtained with five different fuzzy multi-criteria decision making (F-ARTASI, F-MABAC, F-TOPSIS, F-VIKOR, F-MOORA) methods are presented comparatively. In this graph structure, where the alternatives closest to the center perform best, the adaptive control strategy generally ranked first, showing superior performance in most methods. However, remarkably, the sliding mode control strategy was ranked first with the lowest utility value in both F-ARTASI and F-VIKOR methods. This result indicates that the sliding mode control approach performs more effectively in certain evaluation methods and stands out among the alternatives.

On the other hand, the back-stepping control strategy reached the highest utility values by being in the outermost ring in all methods and was evaluated in the last place in each method. The P, PI, PD, PID control strategy, on the other hand, was generally ranked at the bottom and its performance was limited. Intelligent and fuzzy control strategies in the middle ranks varied according to the evaluation methods. These findings reveal that although there are differences in the ranking of alternatives due to some methods, in general, the decision model produces consistent results and especially sliding mode and adaptive control strategies stand out.

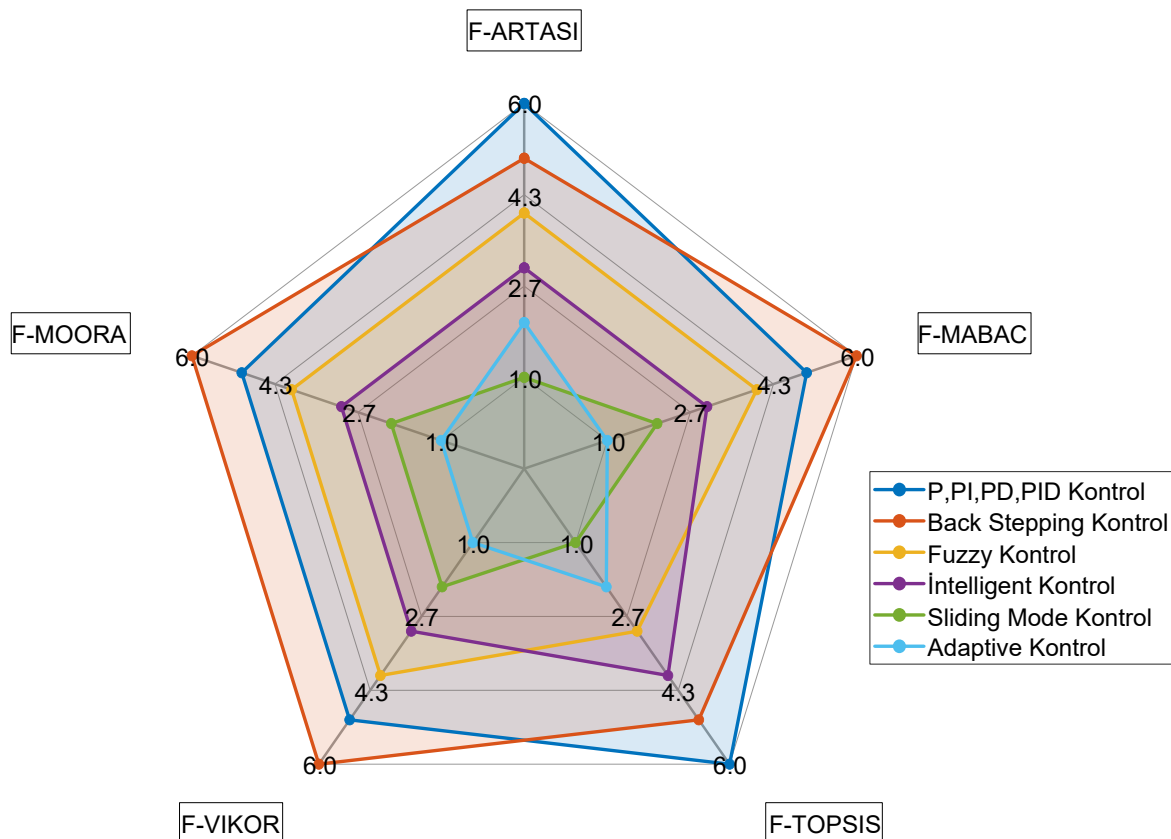


Fig. 6. Visual comparison of F-MABAC, F-TOPSIS, F-VIKOR and F-MOORA

5. Conclusion

Controller selection is a complex multi-criteria decision-making problem, especially in advanced engineering systems such as unmanned ground vehicles (UGVs). In this study, six alternative controllers: PID, backstepping, fuzzy, intelligent, sliding mode, and adaptive controller were evaluated based on seven comprehensive criteria identified in consultation with domain experts. The study employed an integrated fuzzy AHP and fuzzy ARTASI approach to systematically determine the most suitable controller for trajectory tracking in UGVs.

In the first phase of the study, the fuzzy AHP method was used to derive the weights of the criteria by incorporating expert judgments. In the second phase, the fuzzy ARTASI method was applied to evaluate and rank the controller alternatives. According to the results, sliding mode control emerged as the best-performing controller, closely followed by adaptive control. These two controllers stood out due to their robustness, adaptability, and effectiveness in managing nonlinear dynamics and external disturbances, which are critical in UGV applications.

In addition, a sensitivity analysis was conducted to evaluate the stability of the ranking results under different β parameter values. The findings indicated that while sliding mode control is more effective at lower uncertainty levels ($\beta = 0.1-0.4$), adaptive control becomes the most favourable alternative under higher uncertainty ($\beta \geq 0.5$). This highlights the dynamic nature of controller performance based on the system's operating conditions and reinforces the importance of hybrid controller strategies in real-time environments.

To further validate the findings, the results obtained via the F-ARTASI method were compared with those derived from other well-established fuzzy MCDM methods: F-MABAC, F-TOPSIS, F-VIKOR, and F-MOORA. The comparative analysis confirmed the robustness and consistency of the proposed

approach, showing general agreement in the rankings across all methods. This comprehensive multi-method evaluation strengthens the credibility and reliability of the study outcomes.

This study is believed to offer a novel methodological contribution to the literature, as there is a noticeable gap in multi-criteria-based controller selection frameworks for UGV trajectory tracking. The proposed approach can serve as a valuable decision-support tool for researchers and practitioners working on autonomous vehicle systems.

Suggestions for future research include increasing the number of controller alternatives and incorporating additional evaluation criteria. Moreover, emerging MCDM techniques such as MARCOS, CRITIC, or BWM could be explored for enhanced robustness in future studies.

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Conflicts of Interest

The authors declare no conflicts of interest.

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