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Spacecraft tracking control and synchronization: An assessment of conventional, unconventional, and combined methods

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Abstract

Artificial intelligence (AI) promises breakthroughs in space operations, from mission design planning to satellite data processing and navigation systems. Advances in AI and space transportation have enabled AI technologies in spacecraft tracking control and synchronization. This study assesses and evaluates three alternative spacecraft tracking control and synchronization (TCS) approaches, including non-AI TCS methods, AI TCS methods, and combined TCS methods. The study proposes a hybrid model, including a new model for defining weight coefficients and interval type-2 fuzzy sets based combined compromised solution (IT2FSs-CoCoSo) to solve the spacecraft TCS problem. A new methodology is used to calculate the weight coefficients of criteria, while IT2FSs-CoCoSo is applied to rank the prioritization of TCS methods. A comparative analysis is conducted to demonstrate the performance of the proposed hybrid model. We present a case study to illustrate the applicability and exhibit the efficacy of the proposed method for prioritizing the alternative TCS approaches based on ten different sub-criteria, grouped under three main aspects, including complexity aspects, operational aspects, and efficiency aspects. AI and non-AI methods combined are the most advantageous alternative, whereas non-AI methods are the least advantageous, according to the findings of this study.

Keywords: Artificial intelligence; Tracking control; Synchronization of spacecraft; Interval type-2 fuzzy sets; Multi-criteria decision making; CoCoSo

1. Introduction

Future spacecraft is expected to make faster and sharper maneuvers with a quicker response time to unexpected environmental factors (Terui, 1998). In addition, the space environment contains various unknowns, uncertainties, environmental factors, and control input limitations, which alter the speed of such enhanced future spacecraft development. Therefore, spacecraft tracking control and synchronization need to be developed, reliable, and stable to improve spacecraft technologies. As an inference, with a stable and high-performance control mechanism, the future of space transportation and spacecraft is brighter.

Artificial intelligence (AI) is a new technology that is being used in a variety of fields, from medicine to space technology (Zhang et al., 2017; Izzo et al., 2019). AI technology is a promising solution for dealing with unstable

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tracking control and synchronization methods. The ability of the algorithm to make fast and accurate decisions in complex situations is enabled by the use of various new technologies in the decision mechanism of artificial intelligence (Salehi and Burgueño, 2018). Furthermore, traditional methods are risky because the number of unknowns is large, so conventional methods have a high failure rate. On the other hand, there are some drawbacks to employing AI methods. For example, to use artificial intelligence technologies, a large amount of data is required so that the algorithm can be prepared for unexpected events (Haenlein and Kaplan, 2019).

This study evaluates three alternative tracking control and synchronization methods for spacecraft, using AI, non-AI, and AI and non-AI combined. The evaluation is done by conducting a questionnaire with experts in the field. The questionnaire results are then assessed using the proposed MCDM (multi-criteria decision-making) algorithm, and the advantage prioritization is performed. One uniqueness of the study is providing a guide for the decision-makers of spacecraft technologies. Only a few studies compare different control mechanisms, including AI systems, for space transportation in the literature. Therefore, applying this study's methodology is promising in selecting the most advantageous tracking control and synchronization system for spacecraft.

1.1. The objective of the study

Although the world has entered the space age in the twenty-first century, signs of life on extraterrestrial planets are still sought. One of these innovations is the establishment of a colony on Mars. However, transportation from earth to Mars must be provided most safely and efficiently possible to establish a colony on another planet. Using spacecraft is required. Spacecraft can travel to another planet, as well as to earth's orbit or other locations. Spacecraft tracking, control, and synchronization are critical for safe, efficient, and long-term journeys. These, however, can be accomplished in a variety of ways. As a result, this study aims to assess the tracking control and synchronization of spacecraft technology using non-AI, AI, or a combination of both methods in terms of the criteria specified by decision-makers in the study.

1.2. The motivation for using interval type-2 fuzzy sets

The fuzzy set theory, a type-I fuzzy set proposed by Zadeh (Zadeh 1965), has been used as an essential part of solution methods because of the uncertainty of expert opinions in decision-making problems (Türk et al., 2021). Zadeh (1975) introduced type-2 fuzzy sets with additional degrees of freedom to model the uncertainties that type-1 fuzzy sets cannot adequately handle. Type-2 fuzzy sets extend type-1 fuzzy sets (T1FSs), modeling the uncertainty of membership functions, including an extra dimension (Zadeh, 1975). An extra dimension of general type-2 fuzzy sets (T2FSs) which must be maintained in all representations and calculations, causes difficulties, while interval type-2 fuzzy sets (IT2FSs) introduced by Mendel et al. (2006) where the values of secondary memberships are either zero or one, in which case the footprint of uncertainty fully characterizes the type-2 fuzzy sets and the extra dimension may be dropped. Therefore, general type-2 fuzzy sets have some difficulties regarding the semantics of their embedded fuzzy sets. However, interval type-2 fuzzy sets try to overcome these semantic difficulties by restricting the values of the secondary memberships to either zero or one (Garibaldi and Guadarrama, 2011). Therefore, in type-2 sets, there is no restriction on the shape of the footprint of uncertainties (FOUs) and the embedded sets that can be considered acceptable. This causes the loss of the semantic relationship between the type-2 fuzzy set and the concept it models (D'Alterio et al., 2020). The literature indicates that IT2FSs have more advantages over the type-1 fuzzy sets. IT2FSs have been successfully applied to various decision-making problems in the literature, showing that they have more advantages than type-1 fuzzy sets. Therefore, this study aims to present an interval type-2 fuzzy set based on multi-criteria decision-making (MCDM).

Many MCDM methods have been introduced and discussed in the literature to handle decision-making problems. Some of the well-known and frequently used MCDM methods are The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Hwang and Yoon, 1981), Analytic Hierarchy Process (AHP) (Saaty, 1989), Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) (Brans and Mareschal, 1990), Elimination and Choice Expressing REality (ELECTRE) (Roy, 1991), Complex Proportional Assessment (COPRAS) (Zavadskas et al., 1994), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) (Opricovic, 1998), Weighted Aggregated Sum–Product Assessment (WASPAS) (Zavadskas et al., 2012), and Evaluation Based on Distance from Average Solution (EDAS) (Keshavarz Ghorabaee et al., 2015). The Combined Compromised Solution (CoCoSo) approach was introduced by Yazdani et al. (2019) as a novel decision-making method. Weighting Sum Model (WSM) and Weighting Product Model (WPM) was proposed for aggregation strategy. Therefore, this study improves the CoCoSo based on a hybrid model for decision-making problems.

The application of a new methodology for defining weight coefficients of criteria based on defining interrelationships between ranked criteria is proposed. A new methodology has been proposed as it eliminates some shortcomings of classical models for determining the weighting coefficients of the criteria. Among the advantages of the proposed methodology are: (1) it allows decision-makers to have a better perception of the relationship between the criteria, as it considers the relationships between adjacent criteria; (2) allows high consistency of expert comparisons; (3) enables the definition of the weighting coefficients of a larger set of criteria; and (4) comparisons of criteria are not made based on a predefined scale, but the most appropriate scale for presenting expert preferences is defined for each problem considered. This eliminates the limitations of the small range of the nine-point scale used in other subjective models (Saaty, 1980; Rezaei, 2015; Asadabadi et al., 2019).

The CoCoSo model provides a straightforward computational procedure with precise and reliable results to analyze and evaluate decision-making problems. Therefore, this study applies a new methodology for defining weight coefficients of criteria and CoCoSo model with extensions to interval type-2 fuzzy sets.

The rest of the paper is organized as follows. In Section 2, a brief literature review regarding the studies of this study is given. In Section 3, the definitions of the problem, alternatives, and criteria are provided. The proposed methodology and its experimental results with sensitivity and comparative analysis are given in Sections 4 and 5, respectively. In Sections 6 and 7, the results and discussion and the policy implications of this study are presented, respectively. In Section 8, the conclusion of the study is given.

2. Literature review

Spacecraft technology is a relatively new technology that has grown in importance since the twentieth century. As of the twenty-first century, this technology has become even more intense due to human curiosity to explore space and seek life on other planets. Spacecraft, like cars, trains, and engines on land, provide transportation in and out of the atmosphere. It is a problem that these spacecraft are not in a gravity environment and are exposed to meteor fragments while in transit. As a result, artificial intelligence methods are developed for these vehicles to continue operating as efficiently as possible, and non-AI methods are constantly updated. According to the research, a nonlinear control law has been proposed to avoid the obstacles that spacecraft in transit may encounter and make the formation styles most efficient. The most accurate rotation study has been carried out by developing special potential functional methods to avoid obstacles. According to one study, the simulation outputs of their proposed method resulted in advantageous flight configuration and fast-tracking results (Hu et al., 2015a).

In another study, they continued to work on position controls for one or more spacecraft. A finite-time controller was designed by considering the finite-time monitoring attitude. Hence, it has been seen that attitude synchronization is possible in finite time. It aims to reduce possible negativities by proposing a finite-time control law on the routes of spacecraft (Du et al., 2011). Gao et al. (2022) sought to improve the control performance of a straight-line convergence trajectory during rendezvous and docking missions, as well as reduce the energy consumption associated with these operations. The proposed linear combination theorem of the ratio persistence property, which is used to improve time-synchronized control systems, accomplishes this. The simulation results validate the method's efficiency and effectiveness. In another study, a feedback method has been proposed to adapt the spacecraft formation flying system. The proposed method in the study was simulated on over one spacecraft. It was observed that the relative position of the spacecraft led to a non-spherical asymptotic path (Wong et al., 2002). In another study, back-stepping design and neighbor-based design rules are used to synchronize spacecraft attitudes during maneuvers (Du and Li, 2014). Conditions such as actuator saturation and actuator failure were considered in this research on the velocity-independent feedback control problem for a spacecraft. Using the actuator failure information, the researchers devised a system that can handle an error with no angular velocity. Therefore, a numerical example was employed to demonstrate the effectiveness of the proposed tracking system (Xiao et al., 2014).

Another study focusing on the fixed-time monitoring state control problem developed a method to predict unknown disturbances by external disturbances and input inspection. It has been suggested that simulation results support the efficiency of the method developed in the research, and it is a method that can be used (Sun et al., 2019). Zhao et al. (2021) investigated distributed attitude synchronization for flexible spacecraft. The rotation matrix-based controller suggested is a combination of fundamental and additional patterns. Minimum learning parameter techniques are believed to increase the stability of finite time and reduce the computational overhead. Additionally, a surface with a modified sliding mode is used, which has the potential to eliminate singularity. Gao and Wang (2021) offered a fault estimation, and fault-tolerant control technique is offered as a new model. When an actuator malfunction is detected, the objective is to synchronize the follower spacecraft with the leader spacecraft. Numerical practical examples are conducted to identify the success of the model, and it is observed that the model is effective. In another study, the disrupted tracking control problem was examined by considering the disconnections experienced by spacecraft during communication. The study concluded that the tracking and estimation errors converged to zero with the proposed method, considering the Lyapunov-Krasovskii functional approach (Wang et al., 2019). Lawton and Beard (2002) proposed two control strategies have been proposed to prevent spacecraft position alignment failures in or out of earth's orbit. They have shown that it is analytically possible to prevent the problems experienced in position alignment with their proposed method. To the best of the authors' knowledge, no study has evaluated three alternative techniques, including non-AI methods, AI methods, and mixed approaches, for the tracking control and synchronization of spacecraft employing a fuzzy decision-making method.

3. Problem definition

Spacecraft, providing transportation in space technology, is developed and offered for use with one or more methods. These methods can be divided into two non-AI and AI. At the same time, by combining these two titles, both non-AI and AI methods can perform tracking control and synchronization of spacecraft. This is because an incomputable equation in space causes unexpected negative results. Spacecraft's tracking control and synchronization should be done effectively to do it most effectively, and the functionality of the above methods should be evaluated. For this reason, decision-makers need to decide based on different criteria which type of method will be more beneficial for spacecraft. The decision hierarchy of the decision-making problem is shown in Fig. 1.

Novelties in AI technologies have enabled the utilization of AI in tracking control and synchronization (TCS) systems onboard spacecraft. Since each method has its advantages and disadvantages, effectively and efficiently prioritizing the alternatives for selecting the most advantageous one is most important. However, although there are beneficial aspects to using unconventional control methods, there are also benefits to using conventional and combined methods. A thorough examination of the literature review shows a gap in the literature concerning the advantage prioritization algorithm for using alternative TCS methods of spacecraft. Therefore, this study proposes a new multi-criteria decision-making (MCDM) model to prioritize alternative spacecraft TCS methods.

It is undeniable that the number of spacecraft missions will increase as time goes on. Between 1957 and 2016, around 7800 spacecraft were launched (Xie et al., 2016). In the future, this number will increase even further. However, many of these launches could not complete their mission due to various failures. One of these failure types is tracking control and synchronization failure (Zhou et al., 2020). Space is a medium containing many uncertainties and countless risk factors, which increase the failure rate. New tracking control and synchronization methods will emerge with new technologies like AI to make spacecraft missions safer and more successful. However, both old and new TCS methods offer distinct advantages and disadvantages. This creates an opportunity for a decision-making algorithm to prioritize the methods so that decision-makers and policymakers can select the most suitable method based on the spacecraft mission.

3.1. Definition of alternatives

A_1: Non-AI methods: Control and tracking of space vehicles make use of a variety of conventional techniques, including satellite surveillance, marking and flying aircraft, formation flight, and space-based interferometers. On the

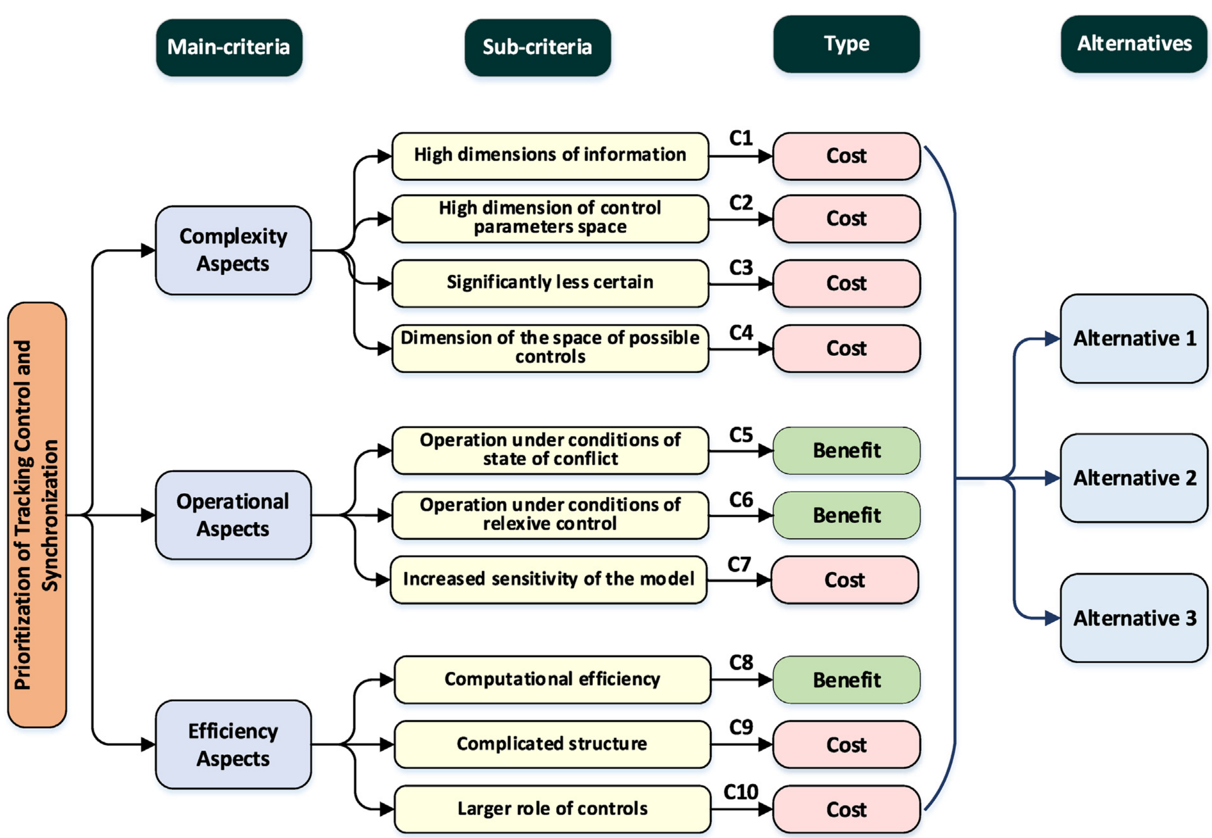

Fig. 1. The hierarchical model.

other hand, to successfully maneuver, spacecraft need to accurately and rapidly detect and carry out a variety of commands. This is one of the most important factors to consider when designing spacecraft. In addition, spacecraft are susceptible to various problems, including control input limitations and actuator failures, which can be a source of uncertainty. This is especially the case when environmental factors are involved. It is an alternative to controlling spacecraft using traditional methods, which do not involve artificial intelligence (Du et al., 2011).

***A_2*: AI methods:** Optimizing the parameters and control variables used in space vehicle tracking and synchronization methods, which is a complex system using artificial intelligence. Considering many data and variables are provided by this method. The security of the control mechanisms that take decisions in the uncertainties encountered in the tracking and synchronization of spacecraft and the high responsibilities make this issue a top priority and concern. It is advantageous to apply artificial intelligence-based control strategies for these systems, and the probability of success is higher than in traditional models. For this reason, using artificial intelligence has become an important alternative for the future (Hasan et al., 2020).

***A_3*: Combined methods:** The ability to make decisions based on more complete data and scenario analysis using an artificial intelligence-based approach in problems such as parameter and variable control, which occur mostly in traditional systems, has created an alternative to integrating these two systems. As a result of this integration, it is anticipated that the security and compliance of the control systems will be enhanced and that current setbacks will be avoided. In complicated systems where artificial intelligence is used, the speed and precision of the process are improved (Fourati and Alouini, 2021).

3.2. Definition of criteria

(1) ***Complexity aspects***

***C_1*: Data complexity (cost):** There is an extremely variable and complex system due to a large amount of data that needs to be reviewed in the tracking and synchronization of spacecraft. There is a lot of information about controlling this system. The fact that environmental and systemic information needs to be obtained in real-time and evaluated in a multidimensional manner complicates the decision-making and implementation processes in the control and follow-up of the spacecraft (Zhang et al., 2020).

***C_2*: Parameter complexity (cost):** It is challenging to manage the resulting system and evaluate different parameters in an integrated manner because of numerous control parameters in the tracking and synchronization of spacecraft. Using variable parameters used in formulas with too many prerequisites causes undesirable results to be obtained (Pellissetti et al., 2006).

***C_3*. Environmental complexity (cost):** Failures and problems in the system's control due to the low rate of giving accurate results of non-linear models, which are used in tracking and synchronizing spacecraft. The low accuracy of the results of the method and the fact that the parameters used can change due to environmental factors make management difficult (De Lara et al., 2006).

***C_4*. Dimensional complexity (cost):** The difficulty in tracking and synchronizing spacecraft is caused by the large number of control parameters that result from taking into account the many different situations that can arise in space. The decrease in the number of dimensions that need to be taken into account in the control of the spacecraft results in the system becoming easier to control and less complex (Chernaya et al., 2016).

(2) ***Operational aspects***

***C_5*. Conflicting operations (benefit):** The continuation of the operation in the conflicts that arise in the operations carried out in the tracking and synchronization of the spacecraft and the interruption of the operation or the absence of communication deficiencies. Artificial intelligence, which combines a range of modern technologies to enable systems to decide in new and unexpected situations, holds a lot of promise for developing smart control policies for complex systems (Truszkowski et al., 2009).

***C_6*. Reflexive operations (benefit):** The continuation of the operations carried out in the space vehicle tracking and synchronization control and the applicability of the desired directions, thanks to the usability of the reflexive control system, which is used to ensure that the desired decision is taken in the decision-making of the system (Jaitner and Kantola, 2016).

***C_7*. Sensitive operations (cost):** As the sensitivity increases in a system, there are situations where the effect of the variable parameters involved in the system's control on the system is high. For this reason, increasing the sensitivity in space vehicle tracking and synchronization is undesirable, where complex and many variables are involved (Gross and Rudolph, 2016).

(3) ***Efficiency aspects***

***C_8*. Computational efficiency (benefit):** Computational efficiency is defined by the amount of time or memory required for a particular step in a computation. Since computers control the tracking and synchronization of spacecraft, these decision-making and computation processes are expected to accelerate, and less memory consumption will occur (Livni et al., 2014).

***C_9*. Dimensional efficiency (cost):** As the number of dimensions to be considered in the control of a system increases, it becomes difficult to optimize the system and obtain the right decision-making processes. The fewer dimensions to consider, the easier it is to control the system (Kravets et al., 2017).

***C_{10}*. Modeling efficiency (cost):** With the fixed parameters used in a mathematical model, the system can be moved without being dependent on variable parameters. In the non-linear method used, disturbance rejection can be specified as undesired outputs. The increase in the effect of these inputs on the system's control makes it difficult to control the system (Gao, 2006).

4. Proposed methodology

This section presents the basic notations of type 1 fuzzy sets, interval type-2 fuzzy sets, and the proposed methodology steps.

4.1. Type-1 fuzzy sets

Definition 1. A type-1 fuzzy set (T1FS) is characterized by a membership function (MF). A T1FS A in T in X is given as:

$$\mu_T : X \rightarrow [0,1] \quad (1)$$

where μ_T denotes the membership function (the degree of membership) of a fuzzy set.

The MF of the T1FSs is crisp. The MFs for both type-1 and blurring type-1 are depicted in Fig. 2 (Mendel, 2007). It can be seen in Fig. 2 that at a given value of$x$, let's sayx', and there is no longer a single value for MF (Mendel et al., 2006).

4.2. Interval type-2 fuzzy sets

As an extension of classical fuzzy sets, Mendel et al. (2006) introduced the concept of interval type-2 fuzzy sets (IT2FSs). Two primary MFs represent a simpler IT2FS: the upper membership function (UMF) and lower membership function (LMF), and each element of these functions is a fuzzy set in$[0,1]$.

Definition 2. A T2FS $\tilde{T}$ in the universe of discourse X is defined by a type-2 membership function$\mu_{\tilde{T}}$, as given in Eq. (2).

$$\tilde{T} = \{(x,u), \mu_{T^{\sim}}(x,u) | \forall_x \in J_x \subseteq [0,1]\} \quad (2)$$
$$0 \leqslant \mu_{T^{\sim}}(x,u) \leqslant 1.$$

Definition 3. T2FS $\tilde{T}$ can be also represented as:

$$\tilde{T} = \int_{x \in X} \int_{u \in X} \mu_{T^{\sim}}(x,u)/(x,u) \quad (3)$$

where $J_x \subseteq [0,1]$ and $\iint$ represent all the possible admissible of the elements$x \in X$.

Definition 4. When $\mu_{\tilde{T}}(x,u) = 1$ for $\forall_x \in X$ and $u \in [0,1]$, then $\tilde{T}$ is called an IT2FSs (Mendel et al., 2006). The set $\tilde{T}$ can be defined as:

$$\tilde{T} = \int_{x \in X} \int_{u \in X} 1/(x,u) \in [0,1] \quad (4)$$

This is a special case of the T2FS and is called IT2FS (Mendel et al., 2006).

Definition 5. Let $T\left(t_1, t_2, t_3, t_4; H_1(\tilde{T}), H_2(\tilde{T})\right)$ be a type-1 trapezoidal fuzzy number where $t_i(1,2,3,4)$ are the points of$x$, $0 \leqslant H_1(T) \leqslant 1$ is the height of the element t_2 and $0 \leqslant H_2(T) \leqslant 1$ is the height of the element t_3 (see Fig. 3 (c)). If the UMF and LMF of an IT2FS $\tilde{T}$ are type-1 trapezoidal fuzzy numbers, then $\tilde{T}$ is called interval type-2 fuzzy numbers (IT2FNs) (Menïz, 2021) (see Fig. Fig. 3 (d)). Then, IT2FNs $\tilde{T}$ can be expressed as follows:

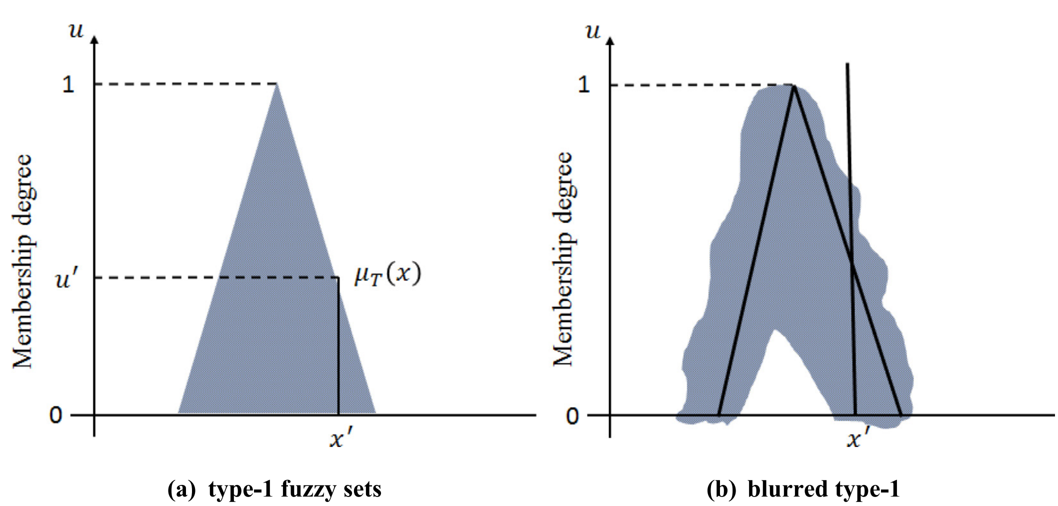

Fig. 2. MFs for type-1 and blurred type-1 fuzzy sets.

$$\tilde{T}_i = \left(\tilde{T}_i^U, \tilde{T}_i^L\right) = \left(\left(t_{i1}^u, t_{i2}^u, t_{i3}^u, t_{i4}^u; H_1(\tilde{T}_i^U), H_2(\tilde{T}_i^U)\right), \left(t_{i1}^l, t_{i2}^l, t_{i3}^l, t_{i4}^l; H_1(\tilde{T}_i^L), H_2(\tilde{T}_i^L)\right)\right) \quad (5)$$

where $\tilde{T}_i^U$ and $\tilde{T}_i^L$, represent the UMF and LMF, respectively. An example IT2FSs is depicted in Fig. 3(a) and Fig. 3(d).

Definition 6. Let $\tilde{T}_1 = \left(\tilde{T}_1^U, \tilde{T}_1^L\right) = \left(\left(t_{11}^u, t_{12}^u, t_{13}^u, t_{14}^u; H_1(\tilde{T}_1^U), H_2(\tilde{T}_1^U)\right), \left(t_{11}^l, t_{12}^l, t_{13}^l, t_{14}^l; H_1(\tilde{T}_1^L), H_2(\tilde{T}_1^L)\right)\right)$ and $\tilde{T}_2 = \left(\tilde{T}_2^U, \tilde{T}_2^L\right) = \left(\left(t_{21}^u, t_{22}^u, t_{23}^u, t_{24}^u; H_1(\tilde{T}_2^U), H_2(\tilde{T}_2^U)\right), \left(t_{21}^l, t_{22}^l, t_{23}^l, t_{24}^l; H_1(\tilde{T}_2^L), H_2(\tilde{T}_2^L)\right)\right)$ be IT2FNs. The arithmetic operations of IT2FNs are defined as follows (Chen and Lee, 2010; Chen and Hong, 2014; Deveci et al., 2020):

(1) The addition of $\tilde{T}_1$ and $\tilde{T}_2$ IT2FNs can be defined as

$$\tilde{T}_1 \oplus \tilde{T}_2 = \left(\tilde{T}_1^U, \tilde{T}_1^L\right) \oplus \left(\tilde{T}_2^U, \tilde{T}_2^L\right) = \begin{pmatrix} t_{11}^u + t_{21}^u, t_{12}^u + t_{22}^u, t_{13}^u + t_{23}^u, t_{14}^u + t_{24}^u; \min\left(H_1(\tilde{T}_1^U), H_1(\tilde{T}_2^U)\right), \\ \min\left(H_2(\tilde{T}_1^U), H_2(\tilde{T}_2^U)\right) \end{pmatrix}, \left(t_{11}^l + t_{21}^l, t_{12}^l + t_{22}^l, t_{13}^l + t_{23}^l, t_{14}^l + t_{24}^l; \min\left(H_1(T^{\sim L}_1), H_1(T^{\sim L}_2)\right), \min\left(H_2(T^{\sim L}_1), H_2(T^{\sim L}_2)\right)\right) \quad (6)$$

(2) The subtraction of $\tilde{T}_1$ and $\tilde{T}_2$ IT2FNs can be defined as.

$$\tilde{T}_1 - \tilde{T}_2 = \left(\tilde{T}_1^U, \tilde{T}_1^L\right) - \left(\tilde{T}_2^U, \tilde{T}_2^L\right) = \begin{pmatrix} t_{11}^u - t_{24}^u, t_{12}^u - t_{23}^u, t_{13}^u - t_{22}^u, t_{14}^u - t_{21}^u; \min\left(H_1(\tilde{T}_1^U), H_1(\tilde{T}_2^U)\right), \\ \min\left(H_2(\tilde{T}_1^U), H_2(\tilde{T}_2^U)\right) \end{pmatrix}, \left(t_{11}^l - t_{24}^l, t_{12}^l - t_{23}^l, t_{13}^l - t_{22}^l, t_{14}^l - t_{21}^l; \min\left(H_1(T^{\sim L}_1), H_1(T^{\sim L}_2)\right), \min\left(H_2(T^{\sim L}_1), H_2(T^{\sim L}_2)\right)\right) \quad (7)$$

(3) The multiplication of $\tilde{T}_1$ and $\tilde{T}_2$ IT2FNs can be defined as.

$$\tilde{T}_1 \otimes \tilde{T}_2 = \left(\tilde{T}_1^U, \tilde{T}_1^L\right) \otimes \left(\tilde{T}_2^U, \tilde{T}_2^L\right) = \begin{pmatrix} t_{11}^u \times t_{21}^u, t_{12}^u \times t_{22}^u, t_{13}^u \times t_{23}^u, t_{14}^u \times t_{24}^u; \min\left(H_1(\tilde{T}_1^U), H_1(\tilde{T}_2^U)\right), \\ \min\left(H_2(\tilde{T}_1^U), H_2(\tilde{T}_2^U)\right) \end{pmatrix}, \left(t_{11}^l \times t_{21}^l, t_{12}^l \times t_{22}^l, t_{13}^l \times t_{23}^l, t_{14}^l \times t_{24}^l; \min\left(H_1(T^{\sim L}_1), H_1(T^{\sim L}_2)\right), \min\left(H_2(T^{\sim L}_1), H_2(T^{\sim L}_2)\right)\right) \quad (8)$$

(4) The arithmetic processes between IT2FNs and crisp value ϕ can be defined as.

$$\phi\tilde{T}_1 == \begin{pmatrix} \phi \times t_{11}^u, \phi \times t_{12}^u, \phi \times t_{13}^u, \phi \times t_{14}^u; \min\left(H_1(\tilde{T}_1^U), H_2(\tilde{T}_2^U)\right), \\ \phi \times t_{11}^l, \phi \times t_{12}^l, \phi \times t_{13}^l, \phi \times t_{14}^l; \min\left(H_1(\tilde{T}_1^L), H_2(\tilde{T}_2^L)\right) \end{pmatrix}, \quad (9)$$

$$\frac{\tilde{T}_1}{\phi} = \begin{pmatrix} \frac{1}{\phi} \times t_{11}^u, \frac{1}{\phi} \times t_{12}^u, \frac{1}{\phi} \times t_{13}^u, \frac{1}{\phi} \times t_{14}^u; \min\left(H_1(\tilde{T}_1^U), H_2(\tilde{T}_2^U)\right), \\ \frac{1}{\phi} \times t_{11}^l, \frac{1}{\phi} \times t_{12}^l, \frac{1}{\phi} \times t_{13}^l, \frac{1}{\phi} \times t_{14}^l; \min\left(H_1(\tilde{T}_1^L), H_2(\tilde{T}_2^L)\right) \end{pmatrix}, \quad (10)$$

4.3. Score function

This section presents a score function of IT2FS based on the concept introduced by Chen et al. (2013) in terms of the ranking value of IT2FS (Hu et al., 2015a,b).

Definition 7. Let $\tilde{H}_i = \left\{\tilde{T} \in \tilde{H} \mid \tilde{T}\right\} = \left(\left(t_1^u, t_2^u, t_3^u, t_4^u; H_1(\tilde{T}_i^U), H_2(\tilde{T}_i^U)\right), \left(t_1^l, t_2^l, t_3^l, t_4^l; H_1(\tilde{T}_i^L), H_2(\tilde{T}_i^L)\right)\right)$ be an IT2FS. Then, the score function is defined by.

$$S\left(\tilde{H}_i\right) = \frac{1}{*\tilde{H}} \sum_{\tilde{T} \in \tilde{H}} score\left(\tilde{T}\right)$$
$$= \frac{1}{*\tilde{H}} \sum_{\tilde{T} \in \tilde{H}} \left[\frac{t_1^u + t_4^u}{2} + \frac{H_1(\tilde{T}_1^U) + H_1(\tilde{T}_2^U) + H_1(\tilde{T}_1^L) + H_2(\tilde{T}_2^L)}{4}\right] \quad (11)$$
$$\frac{t_1^u + t_2^u + t_3^u + t_4^u + t_1^l + t_2^l + t_3^l + t_4^l}{8},$$

where $score\left(\tilde{H}_i\right)$ denote a crisp score.

4.4. Determination of weight coefficients of criteria

The following section presents the original algorithm for determining the weight coefficients of the criteria, which is based on defining interrelationships between ranked criteria. The algorithm for determining the weight coefficients of the criteria is implemented through six steps. The steps are presented in the following part of this paper:

Step 1. Defining criteria. To solve a certain decision-making problem, a set C is defined, which consists of n criteria, $C = \{C_1, C_2, ..., C_n\}$, based on which the selection or ranking of existing alternatives is performed.

Step 2. Ranking of criteria according to their importance. Suppose that h experts representing the set $\aleph_l$ $(l = 1, 2, ..., h)$ participate in the research. Each expert ranks the criteria from set C from the most significant to

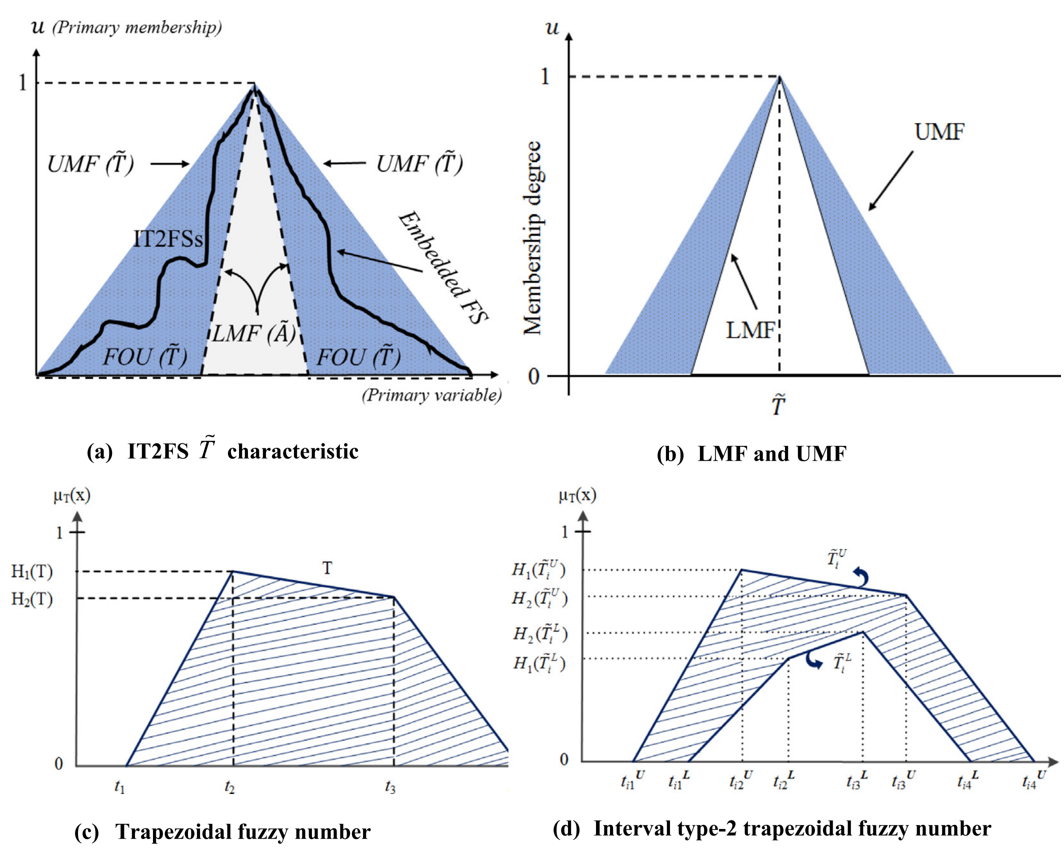

Fig. 3. FOU, LMF, and UMF of ITF2S$\tilde{T}$.

the least important. For the more straightforward presentation of the methodology, we will assume that C_1 is the most influential, while the criterion C_n is the least significant criterion, and the rank $C_1^e \geqslant C_2^e \geqslant C_3^e \geqslant ... \geqslant C_n^e$ is defined where$1 \leqslant e \leqslant h$.

Step 3. Defining the relationship between adjacent criteria. For every-two adjacent criteria, C_j and C_{j+1}, experts define the significance of the relationship $\eta_{j,j+1}^e$ (j = 1,2,. . .,n), where the significance relationship is$\eta_{j,j+1}^e \geqslant 1$. The value of $\eta_{j,j+1}^e$ estimates eth expert () how many times the criterion C_j is more significant than the criterion C_{j+1}. According to the above conditions, we can define the following relations:

$$\begin{aligned} &\tfrac{w_1^e}{w_2^e} = \eta_{1,2}^e; \\ &\tfrac{w_2^e}{w_3^e} = \eta_{2,3}^e; \\ &\quad ... \\ &\tfrac{w_{n-1}^e}{w_n^e} = \eta_{n-1,n}^e; \\ &\tfrac{w_1^e}{w_n^e} = \eta_{1,n}^e. \end{aligned} \tag{12}$$

Step 4. Calculation of weight coefficients of the most important criterion. Based on Eq. (12), we can define the following dependencies between the criteria:

$$\begin{aligned} &w_2^e = \tfrac{w_1^e}{\eta_{1,2}^e}; \\ &w_3 = \tfrac{w_2^e}{\eta_{2,3}^e} = \tfrac{w_1^e}{\eta_{1,2}^e \cdot \eta_{2,3}^e}; \\ &\quad ... \\ &w_n^e = \tfrac{w_1^e}{\eta_{1,2}^e \cdot \eta_{2,3}^e \cdot ... \cdot \eta_{n-1,n}^e} \end{aligned} \tag{13}$$

Based on Eq. (13) and the condition that it is$\sum_{j=1}^n w_j = 1$, we can define the weight coefficient of the most important criterion as follows:

$$w_1^e + \frac{w_1^e}{\eta_{1,2}^e} + \frac{w_1^e}{\eta_{1,2}^e \cdot \eta_{2,3}^e} + ... + \frac{w_1^e}{\eta_{1,2}^e \cdot \eta_{2,3}^e \cdot ... \cdot \eta_{n-1,n}^e} = 1 \tag{14}$$

that is:

$$w_1^e = \frac{1}{1 + \frac{1}{\eta_{1,2}^e} + \frac{1}{\eta_{1,2}^e \cdot \eta_{2,3}^e} + ... + \frac{1}{\eta_{1,2}^e \cdot \eta_{2,3}^e \cdot ... \cdot \eta_{n-1,n}^e}} \tag{15}$$

Step 5. Calculation of weighting coefficients of the remaining criteria. By applying Eq. (13), the weighting coefficients of the other criteria $w_2, w_3, ..., w_n$ for each expert are obtained. The aggregation of expert estimates of the weighting coefficients of the criteria is performed by applying the Eq. (16):

$$w_j = \sum_{l=1}^{h} w_j^l - \frac{\sum_{l=1}^{h} w_j^l}{1 + \left\{ \sum_{l=1}^{h} \omega_j^l \left(\frac{f\left(w_j^l\right)}{1 - f\left(w_j^l\right)} \right)^{\varphi} \right\}^{1/\varphi}} \tag{16}$$

where ω_j^l represents the expert weight coefficients ($l = 1, 2, ..., h$), while$f\left(w_j^l\right) = w_j^l / \sum_{l=1}^{h} w_j^l$.

Step 6. Quality assessment of defined characteristics. The quality of the defined assessment is determined based on the significance ratio of the most significant and the least significant criterion ($\eta_{1,n}$). The value of the least significant criterion can also be obtained from the relation (13):

$$w_n^k = \frac{w_1}{\eta_{1,n}} \tag{17}$$

where w_n^k represents the control weighting factor of the criterion C_n.

Values w_n and w_n^k should be approximately equal. A deviation check is performed by applying the following expression:

$$d_n = \left| 1 - \frac{w_n}{w_n^k} \right| \tag{18}$$

where d_n represents the value of the deviation of the weighting coefficients of the criteria C_n.

If the condition that $0 \leqslant d_n \leqslant 0.1$ is satisfied, then the estimates of the relationship between the significance of adjacent criteria are well defined, i.e., satisfactory. If $d_n > 0.1$ it is necessary to define new relationships between criteria.

4.5. Proposed methodology for alternatives ranking

In this section, we present the steps of the integrated MAIRCA and CoCoSo based on interval type-2 fuzzy sets.

Step 1. Define the alternatives, criteria, and decision-makers (DMs) to structure the proposed model. Let $A_i = A_1, A_2, ... A_n$ having $(i = 1, 2, ... n)$ be set of alternatives, $C_j = C_1, C_2, ..., C_m$ having $(j = 1, 2, ..., m)$ be set of criteria, and $E_y = E_1, E_2, ... E_e$ having $(y = 1, 2, ..., e)$ be set of decision-makers.

Step 2. Build the interval type-2 fuzzy decision matrices $\left(\tilde{\Delta}_e\right)$ in terms of DMs' opinions$\tilde{\Delta}_e = (\tilde{x}_{ije})_{n \times m}$.

$$\tilde{\Delta}_e = (\tilde{x}_{ije})_{n\times m} = \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_m \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \cdots\cdots & A_n \end{array} \\ \begin{pmatrix} \tilde{x}_{11e} & \tilde{x}_{12e} & \cdots\cdots & \tilde{x}_{1me} \\ \tilde{x}_{21e} & \tilde{x}_{22e} & \cdots\cdots & \tilde{x}_{2me} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{1ne} & \tilde{x}_{2ne} & \cdots\cdots & \tilde{x}_{nme} \end{pmatrix} \end{array} \tag{19}$$

Step 3. Compute the aggregated interval type-2 fuzzy decision matrix. The individual decision matrices are aggregated by using the Eqs. (6) and (9),

$$\tilde{x}_{ij} = \left(\frac{\tilde{x}_{ij1} \oplus \tilde{x}_{ij2}, ... \oplus \tilde{x}_{ije}}{e} \right) \tag{20}$$

where $1 \leqslant i \leqslant n$ and$1 \leqslant j \leqslant m$.

$$\tilde{\Delta} = (\tilde{x}_{ij})_{n\times m} = \begin{matrix} \\ C_1 \\ C_2 \\ \vdots \\ C_m \end{matrix} \begin{matrix} A_1 & A_2 & \cdots\cdots & A_n \\ \end{matrix} \begin{pmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots\cdots & \tilde{x}_{1m} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots\cdots & \tilde{x}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{1n} & \tilde{x}_{2n} & \cdots\cdots & \tilde{x}_{nm} \end{pmatrix} \quad (21)$$

Step 4. Normalize the aggregated interval type-2 fuzzy decision matrix $\tilde{\Delta} = (\tilde{x}_{\hat{i}j})_{n\times m}$ into$\tilde{V} = (\tilde{v}_{\hat{i}j})_{n\times m}$. Normalization values for the *benefit* and the cos *t* criteria are computed by Eqs. (22) and (23), respectively.

$$\tilde{v}^{*}_{ij} = \left(\left(\frac{t^u_{j1}}{t^u_{j*}}, \frac{t^u_{j2}}{t^u_{j*}}, \frac{t^u_{j3}}{t^u_{j*}}, \frac{t^u_{j4}}{t^u_{j*}}; H_1(\tilde{T}^U_1), H_2(\tilde{T}^U_1)\right), \left(\frac{t^l_{j1}}{t^u_{j*}}, \frac{t^l_{j2}}{t^u_{j*}}, \frac{t^l_{j3}}{t^u_{j*}}, \frac{t^l_{j4}}{t^u_{j*}}; H_1(\tilde{T}^L_1), H_2(\tilde{T}^L_1)\right)\right) \quad (22)$$

$$\tilde{v}^{-}_{ij} = \left(\left(\frac{t^u_{j^-}}{t^u_{j4}}, \frac{t^u_{j^-}}{t^u_{j3}}, \frac{t^u_{j^-}}{t^u_{j2}}, \frac{t^u_{j^-}}{t^u_{j1}}; H_1(\tilde{T}^U_1), H_2(\tilde{T}^U_1)\right), \left(\frac{t^u_{j^-}}{t^l_{j4}}, \frac{t^u_{j^-}}{t^l_{j3}}, \frac{t^u_{j^-}}{t^l_{j2}}, \frac{t^u_{j^-}}{t^l_{j1}}; H_1(\tilde{T}^L_1), H_2(\tilde{T}^L_1)\right)\right) \quad (23)$$

where $\tilde{t}_{j*} = \max_i \left(\tilde{t}_{ij}\right)$ and $\tilde{t}_{j^-} = \min_i \left(\tilde{t}_{ij}\right)$ are benefit and cost criteria. They are defined as follows:

$$\tilde{V} = (\tilde{v}_{\hat{i}j})_{n\times m} \quad (24)$$

Step 5. Calculate the score function for each alternative using $\tilde{V} = (\tilde{v}_{\hat{i}j})_{n\times m}$ with the help of Eq. (11).

Step 6. Calculate the total of the weighted comparability sequence (σ_i) for each alternative using Eq. (25).

$$\sigma_i = \sum_{j=1}^{m} w_j \tilde{v}_{ij} \quad (25)$$

Step 7. Calculate the total of the weighted comparability sequence ω_i for each alternative using Eq. (26).

$$\omega_i = \sum_{j=1}^{m} (\tilde{v}_{ij})^{w_j} \quad (26)$$

Step 8. Calculate the relative weight of the alternatives using aggregation score strategies using Eqs. (27)–(29).

$$\delta_{ia} = \frac{\sigma_i + \omega_i}{\sum_{i=1}^{n}(\sigma_i + \omega_i)} \quad (27)$$

$$\delta_{ib} = \frac{\sigma_i}{\min_i \sigma_i} + \frac{\omega_i}{\min_i \omega_i} \quad (28)$$

$$\delta_{ib} = \frac{\sigma_i + (1-\gamma)\omega_i}{\sum_{i=1}^{n}\gamma \max \sigma_i + (1-\gamma)\max \omega_i} \; 0 \leqslant \gamma \leqslant 1 \quad (29)$$

where$0 \leqslant \gamma \leqslant 1$.$\delta_{ia}$, δ_{ib}, and δ_{ic} denote the aggregation score strategies as follows: (i) δ_{ia} is the arithmetic mean of sums of weighted sum method (WSM) and weighted product model (WPM) scores, (ii) δ_{ib} is the sum of relative scores of WSM and WPM, (iii) δ_{ic} is the balanced compromise of WSM and WPM models.

scores.

Step 9. Calculate the overall value δ_i for each alternative with the help of Eq. (30).

$$\delta_i = \sqrt[3]{\delta_{ia}\delta_{ib}\delta_{ic}} + \frac{\delta_{ia} + \delta_{ib} + \delta_{ic}}{3} \quad (30)$$

Step 10. Rank the alternative according to the decreasing values ofδ_i.

5. Experimental results

There are uncertainties about how and where these vehicles will be used, expecting Spacecraft vehicles will be used more in the future. The fact that these vehicles may be encountered in unforeseen situations raises concerns. Therefore, both non-AI and AI methods are recommended to address these concerns. However, in which situations these methods are superior to each other can only be evaluated based on the criteria determined by the decision-makers. Therefore, to understand the importance of the criteria specified in the research, a high level of education, an extremely intense technological development, a free scientific environment, and a position that can invest in space programs have been considered. Decision-makers focus this location on the most efficient, beneficial, and sustainable tracking control and synchronization of spacecraft vehicles. Academic and business specialists are consulted to establish a list of criteria and alternatives. The literature is also reviewed. It was determined that three different options and ten separate criteria should be used.

The face-to-face questionnaire was completed by four specialists, including three male and one female expert. They are industry professionals and academic experts from Istanbul-based organizations and universities with extensive knowledge of mechanical engineering, electrical and electronics engineering, data science, and transportation. Expert 1 is a mechanical engineer with ten years of data science experience. The second expert has seven years of expertise in the field of electrical and electronics engineering. Expert number three has fifteen years of expertise in mechanical engineering. Expert number four is a female academician. For the past 22 years, she has been involved in cutting-edge transportation research with a background in control engineering.

(a) ***Application of algorithm for determining weight coefficients of criteria***

In the following section, the application of the methodology for determining the weight coefficients of the criteria is presented:

Steps 1 and 2. The research involved four experts who ranked criteria from a pre-defined set of criteria, Fig. 1. In Table 1, the experts ranked the criteria according to their significance.

Table 1
Ranking of criteria according to their significance.

Criteria	Rank			
	Expert 1	Expert 2	Expert 3	Expert 4
MC_1	2	2	1	1
MC_2	1	3	3	3
MC_3	3	1	1	2
Model Aspect (MC_1)				
C_1	1	2	4	1
C_2	2	2	3	4
C_3	3	1	1	1
C_4	4	4	2	3
Operation Aspect (MC_2)				
C_5	3	3	2	2
C_6	2	2	3	3
C_7	1	1	1	1
Efficiency Aspect (MC_3)				
C_8	2	3	3	2
C_9	2	1	2	2
C_{10}	1	2	1	1

Step 3: Based on the defined ranks of the criteria, the experts defined the significance of the relationship between successive ranks by criteria. The relationships between the criteria are presented in Table 2.

Steps 4 and 5. Based on the values from Table 2 and Eqs. (12)–(14), we can define the weighting coefficients of the criteria, Table 3.

By applying Eqs. (12)–(14), the values of the weight coefficients of the criteria for each expert were obtained individually. Then, experts' aggregation of weight coefficients was performed using Eq. (16). When calculating the local aggregate weighting coefficients, we adopted the same values of expert weighting coefficients $\omega_l = 1/4$ $(l = 1, 2, ..., 4)$, and we adopted the value $\varphi = 1$. An example of aggregation of local values of the weighting factor C_1 is presented in the following section:

$$w_1 = (0.300 + 0.222 + 0.150 + 0.304) - \frac{(0.300 + 0.222 + 0.150 + 0.304)}{1 + \left\{\frac{1}{4}\left(\frac{0.307}{1-0.307} + \frac{0.228}{1-0.228} + \frac{0.154}{1-0.154} + \frac{0.312}{1-0.312}\right)^1\right\}^{1/1}} = 0.249$$

The accumulation of the remaining local values of the weighting coefficients was performed similarly. Global values of weight coefficients are defined by the possibility of cluster weight coefficients with weight coefficients of appropriate criteria.

Step 6. Using the Eqs. (17) and (18), the quality of the defined significance of the criteria was checked. The verification established that all expert estimates of the weight coefficients of the criteria meet the condition that $0 \leqslant d_n^e \leqslant 0.1$ $(1 \leqslant e \leqslant h)$. Based on the obtained results, we can conclude that expert assessments are consistently

Table 2
Experts' assessments of the interrelationships between the clusters/criteria.

Criteria level	Expert1	Expert2	Expert3	Expert4
Clusters	$\eta_{MC2,MC1} = 1.13$	$\eta_{MC3,MC1} = 1.13$	$\eta_{MC3,MC1} = 1.00$	$\eta_{MC1,MC3} = 1.50$
	$\eta_{MC1,MC3} = 1.14$	$\eta_{MC1,MC2} = 1.14$	$\eta_{MC1,MC2} = 1.6$	$\eta_{MC3,MC2} = 1.20$
MC_1 group	$\eta_{C1,C2} = 1.13$	$\eta_{C3,C1} = 1.75$	$\eta_{C3,C4} = 1.60$	$\eta_{C1,C3} = 1.00$
	$\eta_{C2,C3} = 1.14$	$\eta_{C1,C2} = 1.00$	$\eta_{C4,C2} = 1.25$	$\eta_{C3,C4} = 1.40$
	$\eta_{C3,C4=}1.17$	$\eta_{C2,C4} = 1.33$	$\eta_{C2,C1} = 1.33$	$\eta_{C4,C2} = 1.25$
MC_2 group	$\eta_{C7,C6} = 1.50$	$\eta_{C7,C6} = 1.14$	$\eta_{C7,C5} = 1.14$	$\eta_{C7,C5} = 1.17$
	$\eta_{C6,C5} = 1.20$	$\eta_{C6,C5} = 1.40$	$\eta_{C5,C6} = 1.17$	$\eta_{C5,C6} = 1.20$
MC_3 group	$\eta_{C10,C8} = 1.75$	$\eta_{C9,C10} = 1.13$	$\eta_{C10,C9} = 1.40$	$\eta_{C10,C8} = 2.25$
	$\eta_{C8,C7} = 1.00$	$\eta_{C10,C8} = 1.33$	$\eta_{C9,C8} = 1.67$	$\eta_{C8,C9} = 1.00$

Table 3
The final criteria weights.

Criteria	Expert 1	Expert 2	Expert 3	Expert 4	Aggregated w_j	
					Local w_j	Global w_j
Model Aspect (MC_1)	0.3328	0.3328	0.3810	0.4500	0.3762	–
C_1	0.3000	0.2222	0.1500	0.3043	0.2494	0.0939
C_2	0.2667	0.2222	0.2000	0.1739	0.2175	0.0818
C_3	0.2333	0.3889	0.4000	0.3043	0.3361	0.1265
C_4	0.2000	0.1667	0.2500	0.2174	0.2100	0.0790
Operation Aspect (MC_2)	0.3760	0.2912	0.2381	0.2500	0.2924	–
C_5	0.2500	0.2500	0.3333	0.3333	0.2937	0.0859
C_6	0.3000	0.3500	0.2857	0.2778	0.3043	0.0890
C_7	0.4500	0.4000	0.3810	0.3889	0.4056	0.1186
Efficiency Aspect (MC_3)	0.2912	0.3760	0.3810	0.3000	0.3388	–
C_8	0.2667	0.2609	0.2000	0.2353	0.2416	0.0819
C_9	0.2667	0.3913	0.3333	0.2353	0.3107	0.1052
C_{10}	0.4667	0.3478	0.4667	0.5294	0.4557	0.1544

defined and that the obtained weighting coefficients objectively express expert preferences.

(b) ***Application of IT2FSs based CoCoSo for the ranking of alternatives***

Steps 1–2. Four experts evaluate three alternatives in terms of ten criteria with the help of linguistic terms. These linguistic terms and their corresponding values are given in Table 4. The linguistic assessments of three alternatives in terms of each expert are reported in Table 5.

Step 3. The aggregated interval type-2 fuzzy decision matrix is created using Eqs. (20)–(21). The aggregated fuzzy decision matrix is presented in Table 6.

Step 4. The normalized fuzzy values obtained with Eqs. (22)–(24) and Table 6 are reported in Table 7.

Step 5. This step calculates the score values using the normalized decision matrix (see Table 7) and Eq. (11). The score values are given in Table 8.

Step 6. Each alternative is computed using Eq. (25) with the help of Table 8 and criteria weights (see Table 3) and reported in Table 9.

Step 7. Each alternative is calculated using Eq. (26), Table 8, and criteria weights. The results found are given in Table 9.

Steps 8–9. The overall values of δ_{ia}, δ_{ib} and δ_{ic} are calculated by Eqs. (27)–(30) with the help of Table 9.

The values δ_i are presented in Table 10.

Table 4
The ratings' linguistic terms and their interval type-2 fuzzy numbers (Chen and Lee, 2010).

Linguistic variables	Interval type-2 fuzzy sets
Very poor (VP)	((0, 0, 0, 1; 1, 1), (0, 0, 0, 0.5; 0.9, 0.9))
Poor (P)	((0, 1, 1, 3; 1, 1), (0.5, 1, 1, 2; 0.9, 0.9))
Medium poor (MP)	((1, 3, 3, 5; 1, 1), (2, 3, 3, 4; 0.9, 0.9))
Fair (F)	((3, 5, 5, 7; 1, 1), (4, 5, 5, 6; 0.9, 0.9))
Medium good (MG)	((5, 7, 7, 9; 1, 1), (6, 7, 7, 8; 0.9, 0.9))
Good (G)	((7, 9, 9, 10; 1, 1), (8, 9, 9, 9.5; 0.9, 0.9))
Very good (VG)	((9, 10, 10, 10; 1, 1), (9.5, 10, 10, 10; 0.9, 0.9))

Step 10. The final rank of the alternative according to δ_i is$A_3 \succ A_2 \succ A_1$. From Table 10, It can be seen that A_3 has the highest score while A_1 has the lowest score.

5.1. Sensitivity analysis

In the next section, the analysis of the stability of a multi-criteria model in the case of change in subjectively defined parameters is presented. When defining the initial solution, two parameters were subjectively defined. The parameters were defined based on a consensus of experts, as follows: (1) The value of the parameter $\varphi = 1$ used for the aggregation of the weight coefficients of the criterion, Eq. (16); and (2) The value $\Upsilon = 0.5$ was adopted when defining the third strategy of combining alternatives. Since the parameter Υ should meet the condition$\Upsilon \in [0, 1]$, while the parameter φ should meet the condition $\varphi \geq 1$, the question arises, "*Is the initial solution stable for other values of parameters from the interval* $\Upsilon \in [0, 1]$ *and* $\varphi \geq 1$? ". In the following part, the robustness of the initial solution when a variation of the mentioned parameters is analyzed.

(a) ***Influence of parameter*** φ ***on the ranking results***

The parameter φ represents the stabilization parameter of the aggregation function (16) used to fuse the weight coefficients of the criterion. As previously emphasized, the initial solution is defined based on the weighting coefficients of the criteria specified for the value of the parameter $\varphi = 1$. The value of the parameter $\varphi = 1$ was adopted to simulate the minimum level of risk in the decision-making process. Also, the adopted value is selected due to the simpler calculation of fuzed weighting coefficients.

In the following part, the change of the parameter φ in the interval $1 \leq \varphi \leq 100$ was simulated, and 100 scenarios S_p (p = 1,2,. . .,100) were profitably formed. In S_1, the value $\varphi = 1$ was adopted, while in each subsequent scenario, the value φ is defined based on the condition $\varphi_p = \varphi_{p-1} + 1$ ($p \neq 1$). Fig. 4 (a)–(d) shows the dependence of utility functions of alternatives on the change of the parameter φ.

Table 5
The evaluation of alternatives.

Alternatives	Experts	Criteria									
		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
A_1	E1	G	VG	G	VG	MG	MG	VG	F	VG	VG
	E2	VG	VG	VG	G	F	F	VG	MG	VG	G
	E3	G	G	MG	F	G	G	MG	F	G	G
	E4	MG	MG	VG	G	MG	G	F	MP	G	F
A_2	E1	F	MP	G	MP	G	G	P	MG	MP	VP
	E2	VP	P	F	P	MG	MG	MP	F	MP	F
	E3	MG	F	MP	MP	MG	MG	MP	G	VP	P
	E4	MP	MP	P	P	G	VG	MP	VG	P	MP
A_3	E1	MP	P	P	F	VG	VG	MP	G	P	F
	E2	P	P	MP	P	MG	VG	VP	F	F	MG
	E3	F	MP	F	P	VG	G	P	MG	MP	VP
	E4	MG	P	MP	VP	VG	VG	VP	MG	VP	F

Table 6
Fuzzy decision matrix.

Criteria	A_1	A_2	A_3
C_1	((7;8.75;8.75;9.75;1;1),(7.88;8.75;8.75;9.25;0.9;0.9))	((2.25;3.75;3.75;5.5;1;1),(3;3.75;3.75;4.63;0.9;0.9))	((2.25;4;4;6;1;1),(3.13;4;4;5;0.9;0.9))
C_2	((7.5;9;9;9.75;1;1),(8.25;9;9;9.38;0.9;0.9))	((1.25;3;3;5;1;1),(2.13;3;3;4;0.9;0.9))	((0.25;1.5;1.5;3.5;1;1),(0.88;1.5;1.5;2.5;0.9;0.9))
C_3	((7.5;9;9;9.75;1;1),(8.25;9;9;9.38;0.9;0.9))	((2.75;4.5;4.5;6.25;1;1),(3.63;4.5;4.5;5.38;0.9;0.9))	((1.25;3;3;5;1;1),(2.13;3;3;4;0.9;0.9))
C_4	((6.5;8.25;8.25;9.25;1;1),(7.38;8.25;8.25;8.75;0.9;0.9))	((0.5;2;2;4;1;1),(1.25;2;2;3;0.9;0.9))	((0.75;1.75;1.75;3.5;1;1),(1.25;1.75;1.75;2.63;0.9;0.9))
C_5	((5;7;7;8.75;1;1),(6;7;7;7.88;0.9;0.9))	((6;8;8;9.5;1;1),(7;8;8;8.75;0.9;0.9))	((8;9.25;9.25;9.75;1;1),(8.63;9.25;9.25;9.5;0.9;0.9))
C_6	((5.5;7.5;7.5;9;1;1),(6.5;7.5;7.5;8.25;0.9;0.9))	((6.5;8.25;8.25;9.5;1;1),(7.38;8.25;8.25;8.88;0.9;0.9))	((8.5;9.75;9.75;10;1;1),(9.13;9.75;9.75;9.88;0.9;0.9))
C_7	((6.5;8;8;9;1;1),(7.25;8;8;8.5;0.9;0.9))	((0.75;2.5;2.5;4.5;1;1),(1.63;2.5;2.5;3.5;0.9;0.9))	((0.25;1;1;2.5;1;1),(0.63;1;1;1.75;0.9;0.9))
C_8	((3;5;5;7;1;1),(4;5;5;6;0.9;0.9))	((6;7.75;7.75;9;1;1),(6.88;7.75;7.75;8.38;0.9;0.9))	((5;7;7;8.75;1;1),(6;7;7;7.88;0.9;0.9))
C_9	((8;9.5;9.5;10;1;1),(8.75;9.5;9.5;9.75;0.9;0.9))	((0.5;1.75;1.75;3.5;1;1),(1.13;1.75;1.75;2.63;0.9;0.9))	((1;2.25;2.25;4;1;1),(1.63;2.25;2.25;3.13;0.9;0.9))
C_{10}	((6.5;8.25;8.25;9.25;1;1),(7.38;8.25;8.25;8.75;0.9;0.9))	((1;2.25;2.25;4;1;1),(1.63;2.25;2.25;3.13;0.9;0.9))	((2.75;4.25;4.25;6;1;1),(3.5;4.25;4.25;5.13;0.9;0.9))

Table 7
Normalized fuzzy decision matrix.

Criteria	A_1	A_2	A_3
C_1	((0.23;0.43;0.43;0.79;1;1),(0.32;0.43;0.43;0.59;0.9;0.9))	((0.41;1;1;2.44;1;1),(0.65;1;1;1.54;0.9;0.9))	((0.38;0.94;0.94;2.44;1;1),(0.6;0.94;0.94;1.48;0.9;0.9))
C_2	((0.03;0.17;0.17;0.47;1;1),(0.09;0.17;0.17;0.3;0.9;0.9))	((0.05;0.5;0.5;2.8;1;1),(0.22;0.5;0.5;1.18;0.9;0.9))	((0.07;1;1;14;1;1),(0.35;1;1;2.86;0.9;0.9))
C_3	((0.13;0.33;0.33;0.67;1;1),(0.23;0.33;0.33;0.48;0.9;0.9))	((0.2;0.67;0.67;1.82;1;1),(0.4;0.67;0.67;1.1;0.9;0.9))	((0.25;1;1;4;1;1),(0.53;1;1;1.88;0.9;0.9))
C_4	((0.05;0.24;0.24;0.62;1;1),(0.14;0.24;0.24;0.41;0.9;0.9))	((0.13;1;1;8;1;1),(0.42;1;1;2.4;0.9;0.9))	((0.14;1.14;1.14;5.33;1;1),(0.48;1.14;1.14;2.4;0.9;0.9))
C_5	((0.63;0.76;0.76;0.9;1;1),(0.7;0.76;0.76;0.83;0.9;0.9))	((0.75;0.86;0.86;0.97;1;1),(0.81;0.86;0.86;0.92;0.9;0.9))	((1;1;1;1;1;1),(1;1;1;1;0.9;0.9))
C_6	((0.65;0.77;0.77;0.9;1;1),(0.71;0.77;0.77;0.84;0.9;0.9))	((0.76;0.85;0.85;0.95;1;1),(0.81;0.85;0.85;0.9;0.9;0.9))	((1;1;1;1;1;1),(1;1;1;1;0.9;0.9))
C_7	((0.03;0.13;0.13;0.38;1;1),(0.07;0.13;0.13;0.24;0.9;0.9))	((0.06;0.4;0.4;3.33;1;1),(0.18;0.4;0.4;1.08;0.9;0.9))	((0.1;1;1;10;1;1),(0.36;1;1;2.8;0.9;0.9))
C_8	((0.5;0.65;0.65;0.78;1;1),(0.58;0.65;0.65;0.72;0.9;0.9))	((1;1;1;1;1;1),(1;1;1;1;0.9;0.9))	((0.83;0.9;0.9;0.97;1;1),(0.87;0.9;0.9;0.94;0.9;0.9))
C_9	((0.05;0.18;0.18;0.44;1;1),(0.12;0.18;0.18;0.3;0.9;0.9))	((0.14;1;1;7;1;1),(0.43;1;1;2.33;0.9;0.9))	((0.13;0.78;0.78;3.5;1;1),(0.36;0.78;0.78;1.62;0.9;0.9))
C_{10}	((0.11;0.27;0.27;0.62;1;1),(0.19;0.27;0.27;0.42;0.9;0.9))	((0.25;1;1;4;1;1),(0.52;1;1;1.92;0.9;0.9))	((0.17;0.53;0.53;1.45;1;1),(0.32;0.53;0.53;0.89;0.9;0.9))

Table 8
The score values.

Criteria	A_1	A_2	A_3
C_1	1.717	1.596	1.596
C_2	1.654	1.539	1.427
C_3	0.825	0.682	0.800
C_4	0.168	0.230	0.049
C_5	0.075	0.050	0.158
C_6	1.122	1.122	1.122
C_7	0.185	0.000	0.000
C_8	0.478	0.586	0.636
C_9	0.485	0.713	0.649
C_{10}	0.000	0.000	0.074

The results from Fig. 4 (a)–(c) show that the multi-criteria module is sensitive to changes in the parameter φ. In the presented example, changing the parameter φ does not cause changes in the ranks of alternatives, indicating the initial solution's robustness. Fig. 4 (d) confirms that alternative A_3 retained dominance during the simulation and represents the dominant solution from the considered alternatives.

(b) ***Influence of parameter Υ on the ranking results***

The parameter Υ was used to define the third aggregate score strategy, where the value $\Upsilon = 0.5$ was adopted when

Table 9
The values of weighted sequence and power weight.

Criteria	The values of the weighted sequence (σ_i)			Criteria	The values of power weight (ω_i)		
	A_1	A_2	A_3		A_1	A_2	A_3
C_1	0.062	0.252	0.239	C_1	0.771	0.879	0.874
C_2	0.019	0.152	1.738	C_2	0.723	0.857	1.046
C_3	0.060	0.192	0.518	C_3	0.701	0.811	0.920
C_4	0.028	0.740	0.471	C_4	0.753	0.976	0.942
C_5	0.112	0.135	0.167	C_5	0.828	0.842	0.858
C_6	0.118	0.137	0.173	C_6	0.827	0.838	0.856
C_7	0.021	0.245	1.535	C_7	0.633	0.846	1.052
C_8	0.084	0.160	0.137	C_8	0.816	0.861	0.850
C_9	0.026	0.827	0.317	C_9	0.680	0.980	0.886
C_{10}	0.061	0.635	0.168	C_{10}	0.650	0.932	0.759

Table 10
The overall values of alternatives according to IT2Fs based CoCoSo.

Alternatives	δ_{ia}	δ_{ib}	δ_{ic}	δ_i	Rank
A1	0.229	2.000	0.550	1.558	3
A2	0.354	7.066	0.847	4.040	2
A3	0.417	10.464	1.000	5.595	1

defining the initial solution. Since the parameter Υ can have values from the interval [0,1], the interval [0,1] is divided into 50 segments, thus forming fifty scenarios. In the first scenario, the value $\Upsilon = 0.0$ was adopted. In each subsequent scenario, the value of Υ was defined by applying the condition $\Upsilon_t = \Upsilon_{t-1} + 0.02$, where $(t = 1, 2, \ldots, 50; t \neq 1)$. Fig. 5 (a)–(c) shows the change in the score function of the alternatives over 50 scenarios.

Fig. 5 (a)–(c) shows the individual changes in the score functions of the alternatives over the fifty scenarios. In contrast, Fig. 5 (d) shows the comparative differences in the score of all three alternatives. The results show a dependence of the initial solution on the value of the parameter Υ. Also, the results show that alternative A_3 is the best solution from the considered set. Such results were expected, as alternative A_3 is the dominant solution in all three aggregate score strategies. Also, the analysis showed that alternative A_3 has a good advantage over the other two alternatives (A_2 and A_1). These results indicate a clearly defined relationship between the importance of alternatives and that the initial ranking is confirmed and credible.

5.2. Comparative analysis

Various MCDM techniques, which are widely known and used in the literature, were compared with the ranking results of the proposed model. Fig. 6 shows the rankings

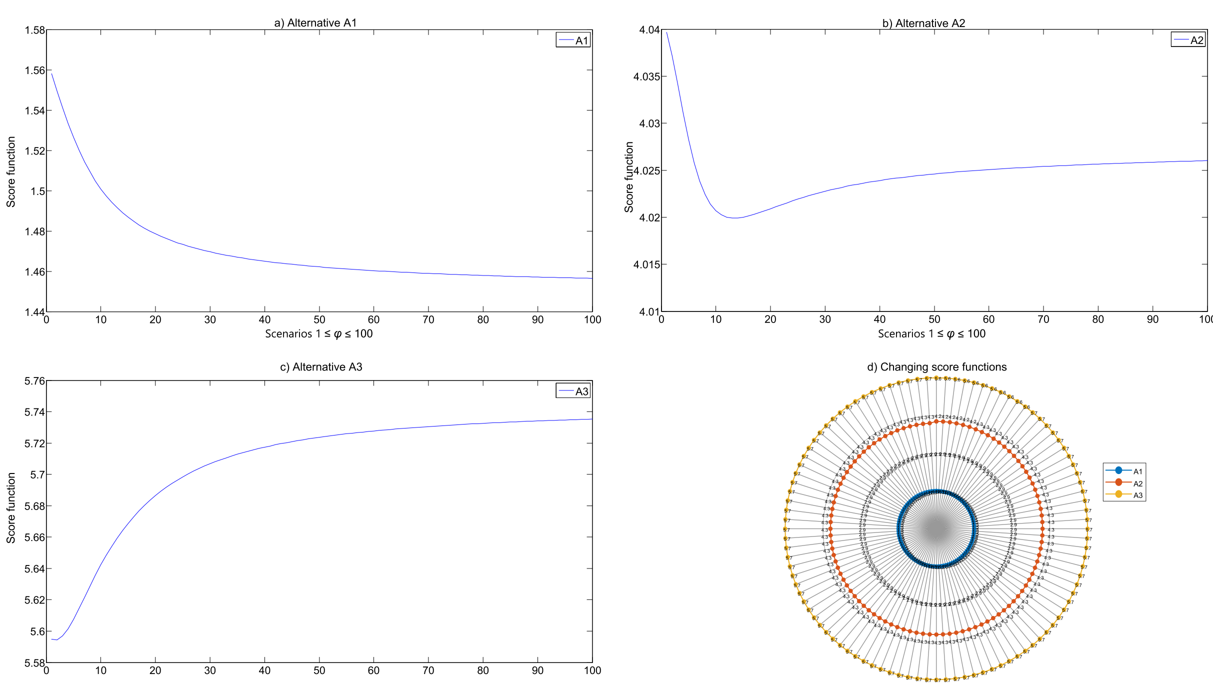

Fig. 4. Dependence of utility functions alternatives to parameter φ changes.

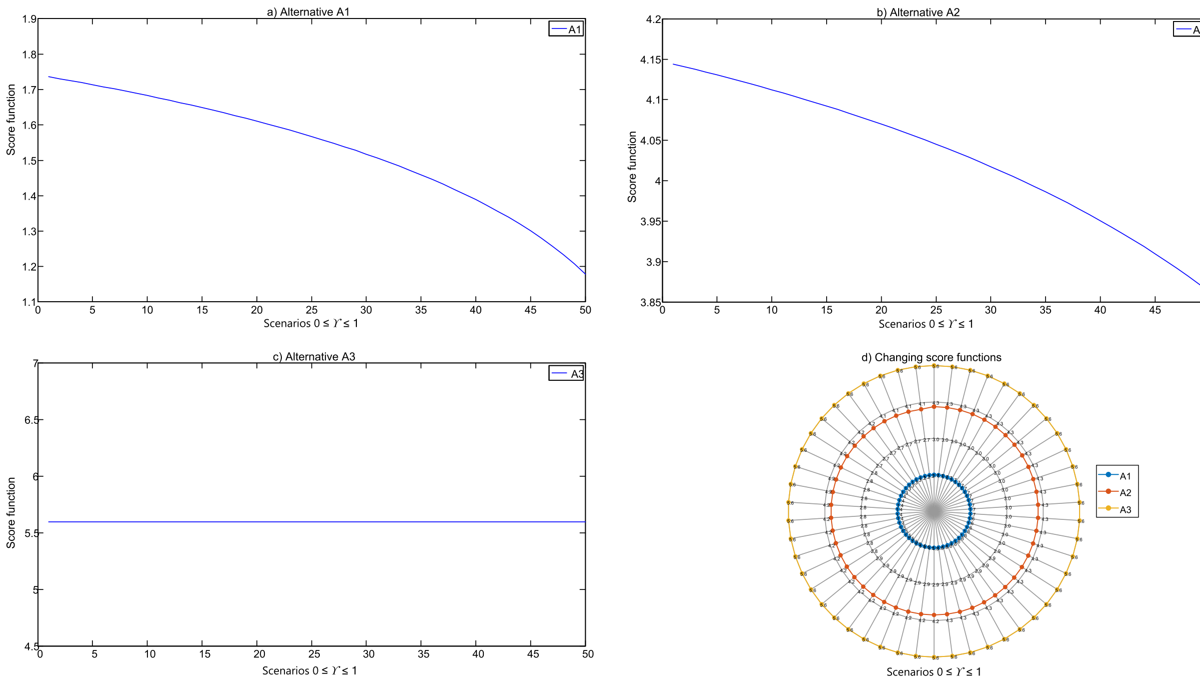

Fig. 5. Change score function alternatives over fifty scenarios.

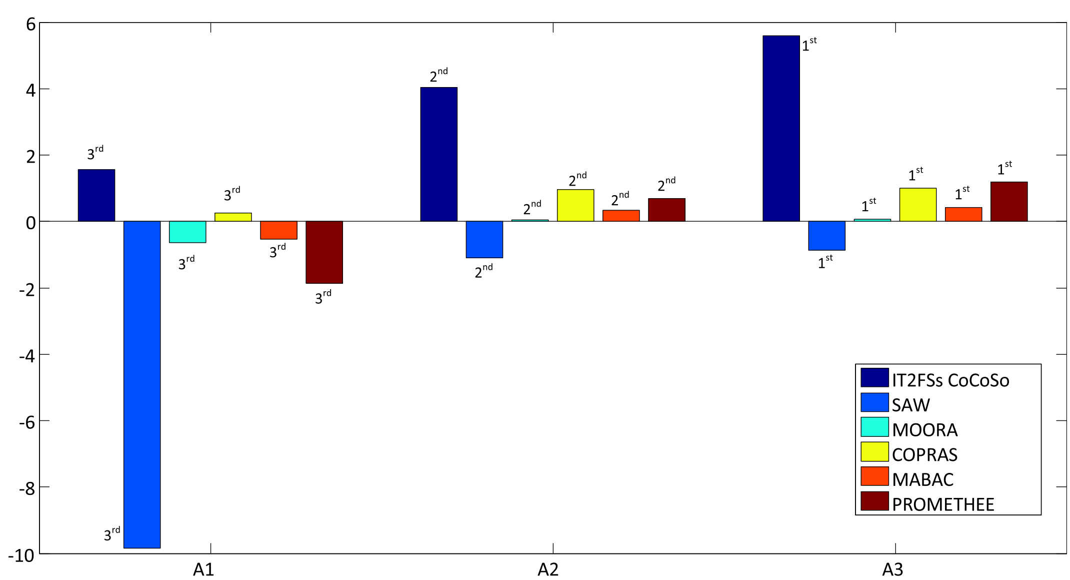

Fig. 6. Ranks of the alternatives based on different fuzzy sets based on MCDM techniques.

obtained using the five MCDM methods. Fuzzy SAW (Kaklauskas et al., 2006), fuzzy MOORA (Brauers and Zavadskas, 2006), fuzzy COPRAS (Ustinovichius et al., 2007), fuzzy MABAC (Pamučar and Ćirović, 2015), and fuzzy PROMETHEE (Brans et al., 1986). It can be seen from this Fig. 6 that the proposed IT2FSs-based multi-criteria decision-making model suggests the same range of alternatives$A_3 \succ A_2 \succ A_1$. In Fig. 6, the comparative analysis gives the robustness of the results of the IT2FSs-based CoCoSo model and the reliability of the proposed alternative selection of A_3.

6. Results and discussion

Tracking control and synchronization of spacecraft using combined (AI +non-AI) methods were found as the most advantageous. Tracking control and synchronization of spacecraft using AI were evaluated as the second most important alternative while tracking control and synchronization of spacecraft using non-AI methods were determined as the most disadvantageous.

It may not be possible for spacecraft to provide the most beneficial efficiency during operation and other activities, only with AI methods. In addition, it was chosen by the decision-makers that the non-AI methods would give the most efficient results for the spacecraft when the AI methods were insufficient. Integrating spacecraft with AI methods can become more efficient with AI methods, which is a method that can constantly improve itself regarding encountered problems. Therefore, it has led it to appear as a more useful alternative to non-AI methods.

Many methods can track, control, and synchronize spacecraft. These methods may have different evaluations among themselves. However, when these methods are divided into categories such as AI and non-AI, it has been determined by the decision-makers participating in the research that non-AI methods will provide less benefit to the problems that may be encountered.

7. Policy implications

Since space technologies are a relatively new sector, authorities are uncertain about how to approach them. Policy implementations can also be problematic because this technology, unlike other technologies, is obsolete and does not appeal to the majority. However, compared to the alternatives presented in this study, it is advantageous that the recommended methods closely resemble modern technology. Since spacecraft technology is a subfield of space technology, this attitude is comparable to that of spacecraft technology. By examining the choices and criteria presented in this research, the disadvantages associated with the use of these technologies can be mitigated. Consequently, if spacecraft technology is insufficient, studying these alternatives will reveal how it will benefit society and influence these technologies.

8. Conclusion

With the space age being the domain of the 21st century, steps are being taken in this age in technology. It is becoming a hot topic with the debates about human beings' interest in the universe and whether they can live outside the world. While transportation on earth is provided by trains, ships, planes, cars, and similar vehicles, this transportation in and out of the atmosphere is done with spacecraft. Spacecraft differ from normal vehicles, and their management has caused different situations. Different methods are used in the management of these vehicles. These methods are divided into two AI and non-AI in this research. This study's results indicate that using AI and non-AI methods combined is the most advantageous strategy, whereas using non-AI methods is the least advantageous.

This study has some limitations in the proposed research framework and can open doors for future studies. In the proposed framework, all data are subjective and based on expert opinions. Any bias in the decision-makers evaluating the alternatives can affect the outcome. Therefore, it is useful to consider some criteria quantitatively. In addition, developing a software-based decision support model is recommended, as the computational complexity of the model will increase when the number of criteria and alternatives increases. In addition, the result obtained in this study can be compared and evaluated with decision-making methods by integrating fuzzy Einstein operators to enrich the evaluations.

The scarcity of studies similar to this study in the literature is one value that makes this study unique. In the following years, humankind's increasing interest in space will increase the importance of this study. Also, the proposed method can be generalized to other decision-making problems such as portfolio selection process, offshore/onshore wind farm site selection, supplier selection, risk assessment, and project evaluation, among others.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Asadabadi, M.R., Chang, E., Saberi, M., 2019. Are MCDM methods useful? A critical review of Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP). Cogent Eng. 6, 1–11.

Brans, J.P., Mareschal, B., 1990. The promethee methods for mcdm; the promcalc, gaia and bankadviser software. In: Readings in Multiple Criteria Decision Aid. Springer, pp. 216–252.

Brans, J.P., Vincke, P., Mareschal, B., 1986. How to select and how to rank projects: the PROMETHEE method. Eur. J. Oper. Res. 24 (2), 228–238.

Brauers, W.K., Zavadskas, E.K., 2006. The MOORA method and its application to privatization in a transition economy. Control Cybern. 35 (2), 445–469.

Chen, T.Y., Chang, C.H., Lu, J.F.R., 2013. The extended QUALIFLEX method for multiple criteria decision analysis based on interval type-2 fuzzy sets and applications to medical decision making. Eur. J. Oper. Res. 226 (3), 615–625.

Chen, S.M., Hong, J.A., 2014. Fuzzy multiple attributes group decision-making based on ranking interval type-2 fuzzy sets and the TOPSIS method. IEEE Trans. Syst. Man Cybern.: Syst. 44 (12), 1665–1673.

Chen, S.M., Lee, L.W., 2010. Fuzzy multiple attributes group decision-making based on the interval type-2 TOPSIS method. Expert Syst. Appl. 37 (4), 2790–2798.

Chernaya, M.M., Shinyakov, Y.A., Osipov, A.V., 2016, June. Spacecraft power system. In: 2016 17th International Conference of Young Specialists on Micro/Nanotechnologies and Electron Devices (EDM). IEEE, pp. 589–593.

D'Alterio, P., Garibaldi, J.M., John, R.I., Pourabdollah, A., 2020. Constrained interval type-2 fuzzy sets. IEEE Trans. Fuzzy Syst. 29 (5), 1212–1225.

De Lara, J., Pérez, F., Alfonseca, M., Galán, L., Montero, I., Román, E., Garcia-Baquero, D.R., 2006. Multipactor prediction for on-board spacecraft RF equipment with the MEST software tool. IEEE Trans. Plasma Sci. 34 (2), 476–484.

Deveci, M., Cali, U., Kucuksari, S., Erdogan, N., 2020. Interval type-2 fuzzy sets based multi-criteria decision-making model for offshore wind farm development in Ireland. Energy 198, 117317.

Du, H., Li, S., 2014. Attitude synchronization control for a group of flexible spacecraft. Automatica 50 (2), 646–651. https://doi.org/10.1016/j.automatica.2013.11.022.

Du, H., Li, S., Qian, C., 2011. Finite-time attitude tracking control of spacecraft with application to attitude synchronization. IEEE Trans. Autom. Control 56 (11), 2711–2717. https://doi.org/10.1109/tac.2011.2159419.

Fourati, F., Alouini, M.S., 2021. Artificial intelligence for satellite communication: a review. Intell. Converged Netw. 2 (3), 213–243.

Gao, Z., 2006. Active disturbance rejection control: a paradigm shift in feedback control system design. American Control Conference. IEEE.

Gao, Y., Li, D., Ge, S.S., 2022. Time-synchronized tracking control for 6-DOF spacecraft in rendezvous and docking. IEEE Trans. Aerosp. Electron. Syst. 58 (3), 1676–1691. https://doi.org/10.1109/taes.2021.3124865.

Gao, Z., Wang, S., 2021. Fault estimation and fault tolerance control for spacecraft formation systems with actuator fault and saturation. Opt. Control Appl. Methods 42 (6), 1591–1611. https://doi.org/10.1002/oca.2751.

Garibaldi, J.M., Guadarrama, S., 2011. Constrained type-2 fuzzy sets. In: 2011 IEEE Symposium on Advances in Type-2 Fuzzy Logic Systems (T2FUZZ). IEEE, pp. 66–73.

Gross, J., Rudolph, S., 2016. Rule-based spacecraft design space exploration and sensitivity analysis. Aerosp. Sci. Technol. 59, 162–171.

Haenlein, M., Kaplan, A., 2019. A brief history of artificial intelligence: on the past, present, and future of artificial intelligence. California Manage. Rev. 61 (4), 5–14. https://doi.org/10.1177/0008125619864925.

Hasan, M.K., Ahmed, M.M., Hashim, A.H.A., Razzaque, A., Islam, S., Pandey, B., 2020. A novel artificial intelligence based timing synchronization scheme for smart grid applications. Wireless Pers. Commun. 114 (2), 1067–1084.

Hu, Q., Dong, H., Zhang, Y., Ma, G., 2015b. Tracking control of spacecraft formation flying with collision avoidance. Aerosp. Sci. Technol. 42, 353–364. https://doi.org/10.1016/j.ast.2014.12.031.

Hu, J., Xiao, K., Chen, X., Liu, Y., 2015a. Interval type-2 hesitant fuzzy set and its application in multi-criteria decision making. Comput. Ind. Eng. 87, 91–103.

Hwang, C.L., Yoon, K., 1981. Methods for multiple attribute decision making. In Multiple attribute decision making. In: Lecture Notes in Economics and Mathematical Systems Book Series (LNE, vol. 186), Springer, Berlin, Heidelberg, pp. 58–191. https://doi.org/10.1007/978-3-642-48318-9_3.

Izzo, D., Märtens, M., Pan, B., 2019. A survey on artificial intelligence trends in spacecraft guidance dynamics and control. Astrodynamics 3 (4), 287–299. https://doi.org/10.1007/s42064-018-0053-6.

Jaitner, M.L., Kantola, H., 2016. Applying principles of reflexive control in information and cyber operations. J. Inform. Warfare 15 (4), 27–38.

Kaklauskas, A., Zavadskas, E.K., Raslanas, S., Ginevicius, R., Komka, A., Malinauskas, P., 2006. Selection of low-e windows in retrofit of public buildings by applying multiple criteria method COPRAS: a Lithuanian case. Energy Build. 38 (5), 454–462.

Keshavarz Ghorabaee, M., Zavadskas, E.K., Olfat, L., Turskis, Z., 2015. Multi-criteria inventory classification using a new method of evaluation based on distance from average solution (edas). Informatica 26 (3), 435–451.

Kravets, P.I., Shymkovych, V.M., Samotyy, V., 2017. Method and technology of synthesis of neural network models of object control with their hardware implementation on FPGA. In: 2017 9th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS), vol. 2. IEEE, pp. 947–951.

Lawton, J.R., Beard, R.W., 2002. Synchronized multiple spacecraft rotations. Automatica 38 (8), 1359–1364. https://doi.org/10.1016/s0005-1098(02)00025-0.

Livni, R., Shalev-Shwartz, S., Shamir, O., 2014. On the computational efficiency of training neural networks. Adv. Neural Inform. Process. Syst. 27, 1–9.

Mendel, J.M., 2007. Type-2 fuzzy sets and systems: an overview. IEEE Comput. Intell. Mag. 2 (1), 20–29.

Mendel, J.M., John, R.I., Liu, F., 2006. Interval type-2 fuzzy logic systems made simple. IEEE Trans. Fuzzy Syst. 14 (6), 808–821.

Menĭz, B., 2021. An advanced TOPSIS method with new fuzzy metric based on interval type-2 fuzzy sets. Expert Syst. Appl. 186, 115770.

Opricovic, S., 1998. Multi-criteria optimization of civil engineering systems. Fac. Civil Eng. Belgrade 2 (1), 5–21.

Pamučar, D., Ćirović, G., 2015. The selection of transport and handling resources in logistics centers using Multi-Attributive Border Approximation area Comparison (MABAC). Expert Syst. Appl. 42 (6), 3016–3028.

Pellissetti, M.F., Schuëller, G.I., Pradlwarter, H.J., Calvi, A., Fransen, S. H.J.A., Klein, M., 2006. Reliability analysis of spacecraft structures under static and dynamic loading. Comput. Struct. 84 (21), 1313–1325.

Rezaei, J., 2015. Best-worst multi-criteria decision-making method. Omega 53, 49–57.

Roy, B., 1991. The outranking approach and the foundations of ELECTRE methods. In Readings in multiple criteria decision aid. Theor. Decis. 31, 49–73. https://doi.org/10.1007/BF00134132.

Saaty, T.L., 1980. The Analytic Hierarchy Process. McGraw Hill, New York.

Saaty, T.L., 1989. Group decision-making and the AHP. In: The Analytic Hierarchy Process. Springer, Berlin, Heidelberg, pp. 59–67.

Salehi, H., Burgueño, R., 2018. Emerging artificial intelligence methods in structural engineering. Eng. Struct. 171, 170–189. https://doi.org/10.1016/j.engstruct.2018.05.084.

Sun, H., Hou, L., Zong, G., Yu, X., 2019. Fixed-time attitude tracking control for spacecraft with input quantization. IEEE Trans. Aerosp. Electron. Syst. 55 (1), 124–134. https://doi.org/10.1109/taes.2018.2849158.

Terui, F., 1998. Position and attitude control of a spacecraft by sliding mode control. In: Proceedings of the 1998 American Control Conference. ACC (IEEE Cat. No.98CH36207). https://doi.org/10.1109/acc.1998.694662.

Truszkowski, W., Hallock, H., Rouff, C., Karlin, J., Rash, J., Hinchey, M., Sterritt, R., 2009. Autonomous and autonomic systems: with applications to NASA intelligent spacecraft operations and exploration systems. In: NASA Monographs in Systems and Software Engineering Book Series, Springer-Verlag London, ISBN: 978-1-84628-233-1. https://doi.org/10.1007/b105417.

Türk, S., Deveci, M., Özcan, E., Canıtez, F., John, R., 2021. Interval type-2 fuzzy sets improved by Simulated Annealing for locating the electric charging stations. Inf. Sci. 547, 641–666.

Ustinovichius, L., Zavadkas, E.K., Podvezko, V., 2007. Application of a quantitative multiple criteria decision making (MCDM-1) approach to the analysis of investments in construction. Control Cybern. 36 (1), 251.

Wang, W., Li, C., Sun, Y., Ma, G., 2019. Distributed coordinated attitude tracking control for spacecraft formation with communication delays. ISA Trans. 85, 97–106. https://doi.org/10.1016/j.isatra.2018.10.028.

Wong, H., Kapila, V., Sparks, A.G., 2002. Adaptive output feedback tracking control of spacecraft formation. Int. J. Robust Nonlinear Control 12 (2–3), 117–139. https://doi.org/10.1002/rnc.679.

Xiao, B., Hu, Q., Zhang, Y., Huo, X., 2014. Fault-tolerant tracking control of spacecraft with attitude-only measurement under actuator failures. J. Guid. Control Dyn. 37 (3), 838–849. https://doi.org/10.2514/1.61369.

Xie, Y.C., Huang, H., Hu, Y., Zhang, G.Q., 2016. Applications of advanced control methods in spacecrafts: progress, challenges, and future prospects. Front. Inform. Technol. Electron. Eng. 17 (9), 841–861. https://doi.org/10.1631/fitee.1601063.

Yazdani, M., Zarate, P., Zavadskas, E.K., Turskis, Z., 2019. A combined compromise solution (cocoso) method for multi-criteria decision-making problems. Manag. Decis. 59 (9), 2501–2519.

Zadeh, L.A., 1965. Information and control. Fuzzy Sets 8 (3), 338–353.

Zadeh, L.A., 1975. The concept of a linguistic variable and its application to approximate reasoning—I. Inf. Sci. 8 (3), 199–249.

Zavadskas, E.K., Kaklauskas, A., Sarka, V., 1994. The new method of multi-criteria complex proportional assessment of projects. Technol. Econ. Develop. Econ. 1 (3), 131–139.

Zavadskas, E.K., Turskis, Z., Antucheviciene, J., Zakarevicius, A., 2012. Optimization of weighted aggregated sum product assessment. Elektronika ir elektrotechnika 122 (6), 3–6.

Zhang, J., Song, Y., Xia, F., Zhu, C., Zhang, Y., Song, W., Xu, J., Ma, X., 2017. Rapid and accurate intraoperative pathological diagnosis by artificial intelligence with deep learning technology. Med. Hypotheses 107, 98–99. https://doi.org/10.1016/j.mehy.2017.08.021.

Zhang, L., Yu, J., Tang, D., Han, D., Tian, L., & Dai, J., 2020. Anomaly detection for spacecraft using hierarchical agglomerative clustering based on maximal information coefficient. In: 2020 15th IEEE Conference on Industrial Electronics and Applications (ICIEA), IEEE, pp. 1848–1853.

Zhao, H., Wu, X., Xie, Y., Du, Y., Zhang, Z., Li, Y., 2021. Rotation matrix-based finite-time attitude synchronization control for flexible spacecrafts with unknown inertial parameters and actuator faults. ISA Trans. https://doi.org/10.1016/j.isatra.2021.10.028.

Zhou, N., Kawano, Y., Cao, M., 2020. Neural network-based adaptive control for spacecraft under actuator failures and input saturations. IEEE Trans. Neural Netw. Learn. Syst. 31 (9), 3696–3710. https://doi.org/10.1109/tnnls.2019.2945920.