Developing Fuzzy-AHP-Integrated Hybrid MCDM System of COPRAS-ARAS for Solving an Industrial Robot Selection Problem

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ABSTRACT

Robots are one of the most commonly used automated material handling equipment (MHE) in an industry, installed to perform a variety of hazardous and repetitive tasks, e.g., loading, unloading, pick-and-place operations, etc. The selection of an appropriate industrial robot is influenced by a number of subjective and objective factors that define its characteristics and working accuracy. As a result, robot selection can be regarded as a multi-criteria decision-making problem. In this article, a new hybrid MCDM model combining COPRAS and ARAS is developed to execute an industrial robot selection process based on three alternatives and five criteria. Fuzzy analytic hierarchy process is integrated to compute the parametric weights. It is discovered that Robot 3 and Robot 1 are coming out to be the best and worst alternative robots from this hybrid model. Finally, comparative analysis among eight other MCDM tools and sensitivity analysis are also performed to assess the stability and robustness of the developed hybrid model and other applied MCDM tools.

KEYWORDS

ARAS, COPRAS, FAHP, Hybrid MCDM, Robot Selection, Sensitivity Analysis

INTRODUCTION

As time passed by, manufacturing concerns are mainly concentrating on the automated-driven systems within an industry. Automation helps to achieve the anticipated goals and can accomplish a tedious task repetitively without disruption. In today's technological advancements, most industries are focusing on lowering production costs while increasing productivity by improving computerized-driven systems. According to Kulak (2005), "the material handling task accounts for 30-75% of the total cost of a

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product, and efficient material handling can be responsible for 15-30% reduction in manufacturing system operations cost" (pp. 310). The robot is a type of computer-programmed automated material handling device mounted to accomplish several types of jobs like loading, unloading, welding, parts assembling, spray painting, picking and placing, etc. Hence, well-organized and efficient handling systems are required to increase material flow efficiency, productivity, system flexibility, improve facility utilization, minimization of lead time and labor cost (Karande and Chakraborty, 2013). Improper selection of industrial robots not only hampers productivity but also puts a negative impression on the organization's status. Therefore, appropriate robots should be selected to enhance production with the highest precision. There are many objective and subjective conflicting criteria are present that can influence the selection of a suitable robot (Mondal and Chakraborty, 2013). Despite the high capital investment, installing robots in industries has many benefits. For example, industrial robots can dramatically enhance the manufacturing organization's efficiency and productivity, it can perform dangerous, complex and repetitive tasks with high accuracy. Bhangale et al. (2004) stated that "there are over 75 attributes that are to be considered while selecting a robot for a particular industrial application". Athawale and Chakraborty (2011) outlined some of the essential variables to consider while picking an appropriate robot alternative, e.g. load-carrying capabilities, manipulator distance, durability, man-machine interface, cost, accuracy, etc. are some of these features. Decision-makers are having difficulty selecting the best robot choice because there are many competing robot performance qualities present, and MCDM coordination is the best solution to these kinds of difficulties.

Because of the advantages listed above, there is an urgent need to resolve this issue and offer the best robot option to be incorporated into an industry, while also providing some simple ideas to the industrial sectors before investing in the installation of automated machinery. When carrying out any robot selection process, the decision maker (DM) must examine many subjective and quantifiable factors, some of which are exploiting (beneficial) or diminishing (non-beneficial) (Rao, 2007). As a result, MCDM techniques are the ideal optimization tools for executing these types of situations with multiple competing criteria. An example of a robot assortment MCDM problem is offered in this research article and evaluated using the newly developed COPRAS-ARAS hybrid MCDM methodology. Several researchers have previously tackled the current robot selection problem using various MCDM strategies (Rao, 2007). Nonetheless, the authors of this paper found all of those studies to be contradictory and inconsistent, implying that there is room for improvement by employing additional viable MCDM methods and comparing the results to the prior ones. According to Lit et al. (2002), "The best way to handle the material is not always clear. In some cases, the requirements are satisfied by several different methods. For this reason, the selection of MHE is a critical stage in the facilities planning or the construction of assembly lines. As several parameters must be considered, some are crucial, and others are more sensitive to design. Therefore, the developer must be given an interactive method, allowing him to easily track the effects of his decisions on the solutions proposed" (p. 331).

MCDM has been used as an effective decision-making technique for several decades. Numerous scholars are always working in this field to improve the MCDM techniques and overcome the shortcomings of prior systems. Even many researchers also developed some new innovative MCDM models for making strategic decisions more precisely and accurately. Day by day, MCDM methods are becoming increasingly popular as a result of their intrinsic ability to evaluate and judge various alternatives, and old traditional MCDM techniques are also becoming obsolete at the same time. A single MCDM tool is insufficient for making an acceptable decision in any complicated decision-making scenario (Karande et al., 2016). Therefore, two or more MCDM models need to be merged to form a hybrid model for taking decisions more effectively. The basic purpose of any hybrid technique is to combine the benefits of two or more MCDM tools into a single model. At the same time, it also helps to overcome the drawbacks of one model by another. In this current research work, the authors took the initiative to combine COPRAS (Zavadskas et al., 2001) and ARAS (Zavadskas and Turskis, 2010) due to their divergent merits, which are thoroughly elucidated in the following section and parallelly endeavored to get rid of the weaknesses of these two models. These two MCDM tools are accompanied by plentiful issues that could be severe in obtaining robust decisions. The disadvantages of the COPRAS method can be described as follows (Kraujalienė, 2019). a) The devoted ranks may differ from those obtained using other methods, b) COPRAS is a sensitive tool, and the results could be affected by a minor change in the data. Similarly, ARAS can only employ beneficial qualities. Thus, cost criteria must first be turned into beneficial elements for ARAS operation, which may lead to contradictory and inconsistent outcomes. COPRAS thankfully corrects this shortcoming, since COPRAS has the property to treat positive and negative parameters separately (Mousavi-Nasab and Sotoudeh-Anvari, 2017). More formally, it is COPRAS's superiority over ARAS, but at the same time, ARAS is more robust and has more stability than COPRAS in the case of parameter weight variation. These explanations supported the conclusion that both of these techniques have their own merits and drawbacks, some of which can be abolished by combining them into one hybrid technique. Generally, COPRAS is a less effective and inferior tool than ARAS and its disadvantages are also more awful than ARAS. Hence, COPRAS's performance needs to be improved and at the same time, some of the weaknesses of these two methods can be eliminated. Thus, by combining these two tools and incorporating some of the critical features of both COPRAS and ARAS, the present hybrid model is established to overcome some of the drawbacks. This hybrid model can yield more pertinent results than these independent methods. More specifically, the COPRAS MCDM's steadiness and performance can be actively enhanced by integrating ARAS with it. The advantages of this newly developed COPRAS-ARAS hybrid model can be explained as follows.

- To improve ranking efficiency, the concept of optimal alternatives is applied.
- The quantitative utility degree is one of the most important components of this hybrid paradigm that is estimated by comparing it to the ideally best variant, which effectively aids in prioritizing alternatives.
- This fusion model is straightforward, requires less computational time, and employs a clear and logical scientific approach.
- The capability of this fusion model to treat maximum and least criteria individually is the most important feature which removes irregularity. As a consequence, it can generate outcomes that are devoid of paradoxes.

In addition to the numerous known MCDM methodologies, the authors of this work propose combining COPRAS and ARAS due to their major benefits over other MCDM tools. First and foremost, let us discuss COPRAS MCDM. COPRAS is used to rank alternatives using a variety of characteristics, including the effectiveness degree of the alternative options and the allied criterion weights (Ayrim et al., 2018). The optimal option in COPRAS is determined by considering both ideal and unideal solutions (Das et al., 2012; Ayrim et al., 2018). These operating principles illustrate that the COPRAS approach is an important MCDM strategy and a powerful decision-making tool. COPRAS grades alternatives based on the influence of cost and benefit type criteria via a single assessment framework, according to Ayrim et al. (2018) "COPRAS differs from other MCDM techniques in that it takes into account the alternative's utility degree, which expresses as a percentage the amount to which one alternative is superior or inferior to the other alternatives utilized for assessment and comparison" (Chatterjee et al., 2011). This information can assist the DM in making a suitable decision (Mulliner et al., 2013). Furthermore, new research specifies that COPRAS-assisted decisions are less biased and more efficient than WSM and TOPSIS decisions (Goswami and Behera, 2021a; Simanaviciene and Ustinovicius, 2012). Still, it is also true that COPRAS can be less stable than WSM in data variation (Kraujalienė, 2019). In addition, COPRAS also has numerous leads over other MCDM tools, including a straightforward and apparent method, significantly less processing time, and a probability of graphical clarification is high. (Das et al., 2012; Ayrim et al., 2018).

On the other hand, ARAS is liable for rating a restricted number of decision options, each of which must be assessed contemporarily in terms of several decision attributes and it does not require any complex mathematical processes. The main advantage of using ARAS MCDM, it effectively helps in prioritizing the alternatives by computing the alternatives' degree of utility compared to the ideal one. Therefore, when this approach is employed, evaluating and rating alternatives becomes considerably easier (Zavadskas and Turskis, 2010). Moreover, Zavadskas and Turskis (2010) also stated that "When the attempt is taken to rank various alternatives and find ways to improve alternative projects, the ratio with an ideal alternative concept can be used." Each MCDM technique has its own merits and demerits. Despite having many drawbacks, the authors of this research felt forced to combine COPRAS and ARAS since the arguments provided were so strong and compelling. Due to the accretion of the benefits and major qualities of these two MCDM methods, the author of this paper feels that the generated fusion model will be much more resilient and robust (Goswami and Behera, 2021a).

The primary purpose of this research is to integrate ARAS with COPRAS, which results in the formation of a combined COPRAS-ARAS hybrid MCDM system applied for tackling a real-world industrial robot selection MCDM problem while seeking to eliminate the flaws of the COPRAS method in order to increase its effectiveness and efficiency. The main goal is to provide the best robot solution among three options for industrialized applications. A completely new hybrid model combining COPRAS and ARAS is developed, and the criteria weights are evaluated using FAHP (Zadeh, 1965; Saaty, 1980) to execute the whole process. Five conflicting criteria are considered in this work, out of which, three are objective (quantitative) criteria, i.e., purchasing cost (PC), load-carrying capacity (LC), and repeatability error (RE). At the same time, the other two, i.e., man-machine interface (MMI) and programming flexibility (PF), are the subjective (qualitative) criteria. Further, the ranking obtained from this hybrid model of COPRAS-ARAS is also cross-verified and validated using eight other MCDM techniques and sensitivity analysis.

LITERATURE REVIEW

For the past few years, MCDM has served as an efficient tool in solving numerous decision-making problems in a wide range of areas. Many researchers have demonstrated its versatility by implementing it in a variety of sectors such as manufacturing (Chatterjee and Chakraborty, 2013), finance (Anyaeche et al., 2017), environment (Yenugula et al., 2023; Yenugula et al., 2024), transportation and health (Sumrit, 2020), for executing complex problems with efficient solutions. Since this study is about industrial robot selection, below are some examples of recent successful MCDM implementations in this field. Chatterjee et al. (2010) used compromise and outranking methods VIKOR and ELECTRE II to solve an industrial robot selection problem. While solving an industrial robot selection problem, Athawale and Chakraborty (2011) investigated the ranking performance of ten well-known MCDM methods. Despite providing nearly identical alternative rankings, WPM, GRA, and TOPSIS outperformed the rest by a small margin. They also came to the conclusion that choosing proper MCDM tools has negligible importance over choosing suitable attributes and alternatives. Mondal and Chakraborty (2013) classified the best robots using four DEA models. Azimi et al. (2014) used the polygon area MADM method for the selection of industrial robots. Karande et al. (2016) investigated the ranking abilities of six major MCDM approaches while analyzing industrial robot selection difficulties. Bairagi et al. (2018) suggested a new multiplicative multiple criterion analysis models for executing a robot selection problem. Kamble and Patil (2018) selected the best alternative robot using the TOPSIS method. Sharaf (2018) solved a robot selection problem using a new decision-making approach based on an ellipsoid algorithm. Wang et al. (2018) established a DSS model that uses TODIM and the cloud model to handle robot selection problems with ambiguous linguistic information. Banerjee et al. (2020) proposed a novel MCDM approach for the ranking and selection of industrial robots. To identify the prominent material-handling mobile robot, AHP, and modified GRA were used by Kumar and Raj (2020). Rashid et al. (2021) integrated the generalized IVF trapezoidal F-BWM method with extended VIKOR and extended TOPSIS to select optimal industrial robots using fuzzy information while considering subjective and objective criteria. Table 1 summarizes some of the additional works of literature on the topic of robot selection issues using various MCDM models.

Table 1. Documented literatures highlighting the applicability of several MCDM approaches for industrial robot selection

References	Year	MCDM Tools Used	Number of Criteria and Alternatives		Particular Application Area
			Criteria	Alternatives	
Shahrabi (2014)	2014	Fuzzy AHP, Fuzzy TOPSIS	8	3	Robot selection for a metal cutting workshop of a truck factory
Khandekar and Chakraborty (2015)	2015	Fuzzy Axiomatic Design (FAD)	9	7	Selection of robots for carrying out light assembly activities efficiently in a manufacturing industry
Parameshwaran et al. (2015)	2015	Fuzzy Delphi, FAHP, FTOPSIS, F-VIKOR	8	3	Robot selection for teaching purpose in mechatronics engineering department
Ghorabaee (2016)	2016	Interval type-2 fuzzy sets, VIKOR	7	8	Selection industrial robots for an auto company
Xue et al. (2016)	2016	Hesitant fuzzy 2-tuple linguistic QUALIFLEX	6	3	Robot selection for a manufacturing company
Yazdani et al. (2017)	2017	MOORA, COPRAS	5	7	Not specified
Liu et al. (2018)	2018	Interval-valued Pythagorean fuzzy, QFD, QUALIFLEX	7	3	Selection of a welding robot for a Chinese auto manufacturing company
Zhou et al. (2018)	2018	Fuzzy AHP, VIKOR	7	3	Selection of mobile robots in healthcare industry
Gundogdu and Kahraman (2020)	2020	Spherical fuzzy AHP	4	4	Not specified
Nasrollahi et al. (2020)	2020	Fuzzy BWM, PROMETHEE	12	4	Not specified
Hornakova et al. (2021)	2021	AHP	7	3	Selection of material handling system
Rashid et al. (2021)	2021	BWM, EDAS	4	5	Not specified

Source: Author(s) own elaboration

Beyond these mentioned works, ARAS and COPRAS approaches have a wide range of applications in a variety of sectors for making strategic judgments. The following section highlights some of the existing research involving ARAS, FAHP, and COPRAS MCDM models. Afful-Dadzie et al. (2016) proposed a hybrid FAHP-PROMETHEE framework to develop aid decision-making programs. Dhiman et al. (2019) used an MCDM method for selecting the optimal alternatives based on three sets of unfavorable criteria to operate a hybrid wind farm. They used COPRAS, TOPSIS, and SAW to determine the best option. Goswami and Mitra (2020) applied AHP-ARAS and AHP-COPRAS MCDM methodologies to select the best mobile model. Ighravwe and Oke (2019) established an integrated F-COPRAS and SWARA approach for ranking the technician's selection factors. Jocic et al. (2020) proposed a cohesive method for selecting e-learning courses based on the symmetry principles and MCDM concept. The PIPRECIA method is used to determine criteria weights, and the IVT F-ARAS method is employed to classify e-learning courses. Khatwani et al. (2015) assessed search channels for internet information using the FAHP-TOPSIS MCDM hybrid system. Matic et al. (2019) developed a new MCDM hybrid system to select and assess suppliers for a construction company in a sustainable supply chain based on 21 criteria. FUCOM is used to determine the criteria weight values. A new rough COPRAS MCDM has been developed to assess the alternatives, which was later verified and confirmed by other MCDM tools like ARAS, WASPAS, WSM, and MABAC.

Mishra et al. (2020) introduced and incorporated SWARA and COPRAS methodologies to choose the best possible bioenergy production technology alternatives.

Salabun et al. (2020) conducted a comparative analysis of four MCDM tools: COPRAS, TOPSIS, VIKOR, and PROMETHEE II. They created a complex benchmarking model by considering additional dimensions during simulation experiments and incorporated various normalization techniques and weighing methods. Shao et al. (2019) proposed a hybrid MCDM system to improve the quality of the information system for research. Rough-numbered COPRAS is used to evaluate the performance of Chinese university research information systems. Singh et al. (2019) used ARAS and TOPSIS techniques to select the best optimum conditions to generate prolific high-quality holes. Valipour et al. (2017) presented an Iranian case study, where they introduced a SWARA-COPRAS hybrid risk assessment framework in a deep-base excavation project. A case study on the selection of staff in a manufacturing company was conducted by Yalcin and Pehlivan (2019) using fuzzy CODAS combined with hesitant fuzzy envelopes based on comparative linguistic expressions (CLEs). A sensitivity study was conducted to show that the ranking results were stable and valid. The obtained rankings have also been compared with different fuzzy MCDM, including F-WASPAS, F-COPRAS, F-EDAS, F-ARAS, and F-TOPSIS. Table 2 also depicts some of the further FAHP, ARAS, and COPRAS-assisted decision-making concerns.

Research Gaps and Novelty: It is obvious from the earlier works that time-consuming traditional tools like PROMETHEE, TOPSIS, ELECTRE, and VIKOR as well as other complex MCDM systems are routinely employed to find the optimal robot options. Conventional MCDM tools are typically inefficient and require extensive mathematical analysis. As a result, a simple integrated MCDM system that produces fair and reasonable outcomes within a quick computation period is urgently needed. Even though the COPRAS and ARAS are two of the most extensively utilized prevalent MCDM tools in decision-making history, very few published research studies are present that employ these two methods together to evaluate an industrial robot selection problem. Furthermore, the hybrid MCDM concept has received very less attention and is rarely investigated by most academics. Although a few hybrid fusion models have been devised in recent years, they are either difficult to understand or unfriendly to users. None of the previous scholars ever attempted to integrate two straightforward and commonly used MCDM methods like COPRAS and ARAS. Therefore, the authors set out to create a simple and systematic FAHP-integrated COPRAS-ARAS hybrid MCDM system to solve this robot selection issue. In addition to this, the ongoing analysis is primarily based on the previous work conducted by Rao (2007), in which the author employed six MCDM tools to rate the three alternatives, but unfortunately, Rao (2007) failed to produce a stable alternative ranking as can be observed in Table 14. The applied methods proposed different rankings and contradictory outcomes. Hence, this research also serves the purpose of resolving the existing research flaws by Rao (2007) and producing a stable ranking using an updated hybrid MCDM system.

The authors of this study took the initiative to blend COPRAS and ARAS to create a novel hybrid model, which had never been done previously. As a result, this article serves the following functions.

- A novel hybrid model is developed by merging ARAS and COPRAS.
- Using this COPRAS-ARAS hybrid model, a suitable industrial robot is proposed among three different possibilities based on five criteria, whereas FAHP is employed to estimate the parametric weights.
- To deal with the errors associated with the previous analysis designed by Rao (2007) and to generate a consistent ranking throughout the analysis.
- Eight additional MCDM tools namely, MULTIMOORA, COPRAS, WPM, MOORA, TOPSIS, WSM, ARAS, and WASPAS are ranked alongside and compared with the hybrid model's ranking.
- Three stages of sensitivity analysis are carried out to validate the outcomes of the methodologies applied.

This robot selection problem is retrieved from prior literature and re-evaluated to reduce the vagueness and uncertainty connected with the previous study while finding the criteria weights using the FAHP weighted estimation technique. Although Rao (2007) previously handled this particular

Table 2. Past literatures involving the applications of FAHP, ARAS and COPRAS in different fields

References	Year	MCDM Models Used			Applicable Area
		Environment	Weighting Tool	Ranking Tool	
Sakthivel et al. (2013)	2013	Fuzzy sets	AHP	PROMETHEE, GRA	Selection of suitable car for an automotive industry
Adali and Isik (2016)	2016	Crisp values	AHP	ARAS, COPRAS	Selection of air-conditioner
Ozbek and Erol (2017)	2017	Crisp values	Equal weights	ARAS, COPRAS	Rating of factoring companies
Barak and Dahooei (2018)	2018	Fuzzy sets	DEA	ARAS, MULTIMOORA, TOPSIS, COPRAS, SAW, VIKOR	Evaluation of airlines safety in aviation sector
Chatterjee et al. (2018)	2018	Grey numbers	DEMATEL	ARAS, TOPSIS, COPRAS	Green Supply Chain Management Performance Evaluation
Dursun and Arslan (2018)	2018	2-tuple fuzzy sets	QFD	COPRAS	Assessment of washing liquid for a Turkish detergent manufacturer
Radovic et al. (2018)	2018	Rough sets	SWARA	ARAS, WASPAS, MABAC, EDAS, SAW	Performance measurement of transportation companies
Kumari and Mishra (2020)	2020	Intuitionistic fuzzy sets	Divergence measure and Entropy	COPRAS	Green supplier selection for a manufacturing company
Ozdogan et al. (2020)	2020	Fuzzy sets	AHP	TOPSIS	Prioritizing mayors for better enhancement of municipal services in Turkey
Rani et al. (2020)	2020	Hesitant fuzzy sets	SWARA	COPRAS	Sustainable supplier selection for a trading firm in India
Yildirim and Mercangoz (2020)	2020	Combined fuzzy and grey numbers	AHP	ARAS	Logistics performance index evaluation of OECD countries
Yildizbasi and Unlu (2020)	2020	Fuzzy sets	AHP	TOPSIS	Using Industry 4.0 to assess the performance of three SMEs

Source: Author(s) own elaboration

decision-making problem by using numerous MCDM techniques, those analyses were found to be inconsistent and unstable, leading the authors to explore the same topic in this paper. The most serious flaw in Rao's (2007) research is that it employs the traditional AHP method to generate the criteria weights, which is an ineffective tool for dealing with uncertain situations. Therefore, the fuzzy concept is used in this study to take into account the vague and indefinite information, to prescribe a more precise and realistic solution to the problem. This study aimed to fill up the research gap and correct flaws in the results of Rao's preceding experiment (2007).

It is evident from the discussed literature that AHP is a widely used MCDM tool for estimating criteria weights in various research fields. However, because human preference is blemished by ambiguity, uncertainty, and vagueness in most practical situations, DMs find it harder to assign accurate numerical values for comparing decisions explicitly (Liu and Zhang, 2011; Ouma et al., 2017). Hence, the DM would have difficulty expressing the strength of his preferences and confidence in pair-wise comparison judgments in the traditional AHP method (Ouma et al., 2017). As a result, it has been argued that AHP is ineffective when applied to ambiguously or vague real-life problems involving uncertainty, insecurity, and subjectivity (Deng, 1999). Conventional AHP tools cannot effectively handle problems with such elusive, imprecise, and incomplete information, mainly when the problem includes both qualitative and quantitative factors, as in this case. The fuzzy set concept can be used to deal with uncertainty, imprecision, and subjectivity in decision-making processes. By quantifying and representing incomplete information using a membership grade function, the fuzzy concept formalizes human behavior's subjective and imprecise nature (Zadeh, 1965). The benefit of fuzzy-based pair-wise comparison is that it permits DMs to be more flexible in their decisions. It is achieved by varying degrees of fuzzification (Ouma et al., 2017).

Furthermore, suppose the expert is unsure about the extent to which decisions are important. Therefore, FTS can overlap the criteria preferences expressed by a membership function, and interval decisions are provided as an expression of the fuzzy membership function (Kordi, 2012). Fuzzy pair-wise comparison perception can be integrated with AHP to accommodate ambiguity in professionals' heuristics and account for judgment subjectivity (Mikhailov, 2003). DM's levels of confidence and risk-taking attitudes should be considered (Ouma et al., 2017). For the reasons stated FAHP is found suitable for this analysis to estimate the parametric weights. Overall, this research work is unusual in that it addresses an industrial robot selection problem for the first time utilizing a newly designed hybrid MCDM tool that combines COPRAS and ARAS MCDM methodologies, while concurrently satisfying the research gaps and eliminating contradictions from past publications.

Designing of the Decision-Making Framework

Designing a MCDM research framework entails synthesizing current knowledge and identifying critical factors for building a comprehensive structure. The following procedures can be taken to design the research framework for the ongoing MCDM analysis.

Step 1 **(Defining of Research Objectives):** The first stage is to specify the research goals for the given problem. The fundamental purpose of this research can be defined as the construction of a novel COPRAS-ARAS hybrid MCDM model for selecting an appropriate industrial robot among three choices based on five competing criteria.

Step 2 **(Formation of an Expert Committee):** A committee is formed comprising 6 expert members having high expertise in the field. The panel members include the present authors (2 authors) and 4 experts from different industries having high exposure to the field of robotics. The authors have invited 4 industrial professionals to take part in this survey and ask them to provide their judgments on the performance of attributes. The invited experts have high knowledge and more than 15 years of industrial experience. All the details about the panel board members are presented in Table 3.

Table 3. Details of the panel expert members

Experts	Industry	Designation	Experience
Expert 1	Manufacturing	Vice-president	18
Expert 2	Healthcare	Chief medical supervisor	22
Expert 3	Robotics	AI scientist	20
Expert 4	Transportation	General manager	16
Author 1	Academician	Researcher	5
Author 2	Academician	Professor	15

Source: Author(s) own elaboration

Step 3 **(Conducting Brainstorming Session):** Several brainstorming sessions have been conducted to identify the essential parameters influencing the appropriate selection of robots for industrial purposes. Reputed international databases like Scopus and Web of Science (WoS) are mostly used to perform a thorough evaluation of previously published papers. International peer-reviewed journals with high Impact Factor (IF) like Symmetry (IF: 2940), Robotics and Computer-Intergrated Manufacturing (IF: 10.103), International Journal of Industrial Engineering Computations (IF: 3.271), Fuzzy Sets and Systems (IF: 4.462), International Journal of Production Research (IF: 9.018), Expert Systems with Applications (8.665) are mainly followed to adopt some ideas for the current analysis. Some specific keywords have been used to search the leading databases like 'industrial robot selection', 'MCDM applications', 'robot selection using MCDM', 'industrial applications of MCDM', 'hybrid MCDM', etc. These keywords result in 24,700 published articles from the Scopus database, making it difficult for the DM's to sort out the important ones. As a result, several filters were used to remove the articles that were unnecessary from the list. Finally, the panel experts came up with 150 articles that have been studied thoroughly to identify the important parameters that adversely affect industrial robot selection. Furthermore, the research papers published in high IF journals in recent five years have been only referred to. Particularly, one article by Rao (2007) grab the author's attention and they found several flaws that lack the research outcomes.

Step 4 **(Define Decision Criteria):** Five important criteria have been finally specified that are used to evaluate three alternative robots. These criteria were deemed by the expert members to be highly relevant to the research objectives and strongly reflect the performance of the alternatives. Both quantitative and qualitative criteria have been considered here for analyzing the performance of the robot alternatives.

Step 5 **(Selection of Evaluation Methods):** Various MCDM methods used previously by past researchers have been reviewed. The committee members found that the prior works mainly adopt outdated traditional tools that are incompetent in producing effective decisions. After conducting rigorous in-depth research of some MCDM models, the experts discovered that COPRAS and ARAS are stronger and provide substantial benefits when compared to other methodologies. Additionally, these two evaluation techniques are also appropriate based on the nature of the decision problem, the available data, and the preferences of the decision-makers.

Step 6 **(Considering Decisions Under Uncertainty):** Decision-making processes often involve uncertainties, and thus the fuzzy concept is introduced to handle the vague and ambiguous condition associated with the ongoing robot selection problem.

Step 7 **(Conducting Sensitivity Analysis):** Three stages of sensitivity analysis were performed to assess the robustness of the models used. Sensitivity analysis allows professionals to detect variations in the output results for any changes made in the input data.

Step 8 **(Validate the Applicability of the Hybrid Model):** The final result produced by the hybrid model is also validated by comparing it with results obtained from eight other MCDM models.

Step 9 **(Document and Communicate the Framework):** The MCDM research framework is documented in a clear and concise manner. Detailed explanations of each component, the relationships between them, and the decision-making process are well explained. The framework is effectively communicated to ensure its adoption and understanding by researchers and practitioners.

MATERIALS AND METHODS

Rao (2007) first considered this robot section problem and applied GTMA, WSM, WPM, TOPSIS, and modified TOPSIS to analyze the best robot while considering three alternatives and five selection criteria. Among these five criteria, LC, MMI, and PF are the beneficial criteria (maximum), whereas PC and RE are the non-beneficial (minimum) criteria. The identical robot selection dilemma is addressed once again in this context. An appropriate robot has to be chosen for food packaging purposes in the Indian food and beverage processing industry. Tenders from three reputable robot manufacturing companies have been requested for the case study and the three alternative robots are designated as RB1, RB2, and RB3 to protect the company's identity. To rank the robot options, a new hybrid MCDM model integrating COPRAS and ARAS is built, while the five-factor weights are re-evaluated using FAHP. To prove the ability of this new COPRAS-ARAS combined model, the outcome result from this hybrid technique is also cross-checked using eight other MCDM tools and also validated through three stages of sensitivity analysis. Figure 1 depicts the overall framework of the entire investigation using a flowchart approach.

Fuzzy Analytic Hierarchy Process (FAHP)

In 1980, Thomas L. Saaty (1980) first invented the traditional AHP method, which was later extended by incorporating the fuzzy concept (Zadeh, 1965) to develop a new method called FAHP (Buckley, 1985; Chang, 1996) in order to improve consistency and eliminate the errors associated with traditional AHP. Van-Laarhoven and Pedrycz (1983) conducted the first FAHP analysis in 1983, followed by Buckley (1985) in 1985. Buckley (1985) pioneered an innovative geometric mean method for determining the fuzzy weights in 1985, and Chang (1996) contributed the extent analysis method for evaluating the fuzzy weights in 1996. Buckley's geometric mean method (Buckley, 1985) is approved in this article, and the current analysis employs triangular fuzzy number (TFN) shown in Figure 2. FAHP starts with a relative importance matrix ($B = n_i \times n_j$), shown in Table 4. A committee was formed, consisting of various specialist individuals such as CEOs of well-known robot manufacturing companies, researchers, and scientists. The specialist members have over 15 years of field experience and vast expertise in the field of robotics. Following a major brainstorming session, the decision-makers (DM) made a consistent choice and presented their own perspectives on the pair-wise comparisons among the five parameters given in Table 4.

The relative importance matrix in Table 4 is created according to Saaty's nine-pair linguistic scale (Saaty, 1980) shown in Table 5. By comparing the five criteria among each other, the TFNs of their respective crisp values depicted in Table 4 are adjusted according to Figure 3. Table 5 represents Saaty's scale and their respective TFNs. The consistency of the relative importance matrix is also checked following the 6 steps discussed further, and the consistency ratio (CR) is found to be 0.00457 (4.57%), which is well within the limit i.e., less than 10%. All the terminologies closely related to the consistency checking namely, Eigen Vector (EV), average consistency (λ_{max}), Consistency Index (CI) and CR are evaluated in Table 6 using Equation (11) to Equation (15).

Equation (1) expresses the membership function $\mu_{\tilde{N}}(x)$ of a triangular fuzzy number $\tilde{N} = (a, b, c)$ depicted in Figure 2.

$$\mu_{\tilde{N}}(x) = \begin{cases} 0 & for\, x < a \\ \dfrac{x-a}{b-a} & for\, a \le x \le b \\ \dfrac{c-x}{c-b} & for\, b \le x \le c \\ 0 & for\, otherwise \end{cases} \tag{1}$$

Where, a, b, c denotes the real numbers and a < b < c. Figure 2 shows the lower threshold limit as 'a', the middle threshold limit as 'b' and the upper threshold limit as 'c'. Figure 3 represents Saaty's scale in terms of TFN.

Equation (2) to Equation (7) represents some of the essential operational laws and mathematical computation formulas of two triangular fuzzy numbers, say, $\widetilde{N_1} = (a_1, b_1, c_1)$ and $\widetilde{N_2} = (a_2, b_2, c_2)$.

$$\widetilde{N_1} + \widetilde{N_2} = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \tag{2}$$

Figure 1. Flowchart representation of the complete robot selection decision-making analysis
Source: Author(s) own elaboration; created by Autocad 2007

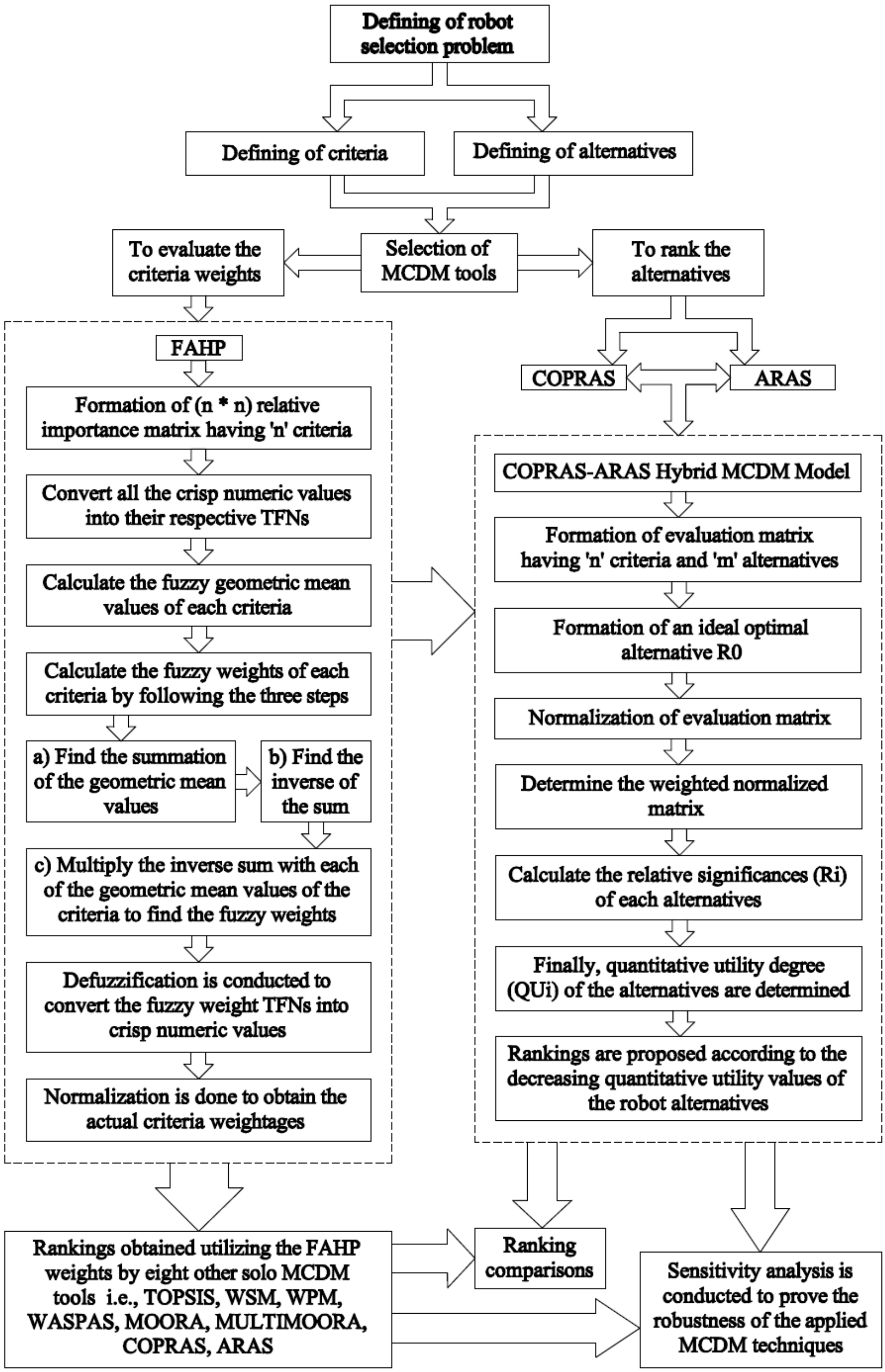


Table 4. Relative importance matrix

Criteria Comparison		PC	LC	RE	MMI	PF
PC	Crisp values	1	5	1	7	5
	TFN	1, 1, 2	4, 5, 6	1, 1, 2	6, 7, 8	4, 5, 6
LC	Crisp values	1/5	1	1/5	2	1
	TFN	1/6, 1/5, 1/4	1, 1, 2	1/6, 1/5, 1/4	1, 2, 3	1, 1, 2
RE	Crisp values	1	5	1	7	5
	TFN	1, 1, 2	4, 5, 6	1, 1, 2	6, 7, 8	4, 5, 6
MMI	Crisp values	1/7	1/2	1/7	1	1/2
	TFN	1/8, 1/7, 1/6	1/3, 1/2, 1/1	1/8, 1/7, 1/6	1, 1, 2	1/3, 1/2, 1/1
PF	Crisp values	1/5	1	1/5	2	1
	TFN	1/6, 1/5, 1/4	1, 1, 2	1/6, 1/5, 1/4	1, 2, 3	1, 1, 2

Source: Author(s) own elaboration; Panel board members

Figure 2. Representation of fuzzy triangular numbers (TFNs)

(Source: Author(s) own elaboration; Created by Autocad 2007)

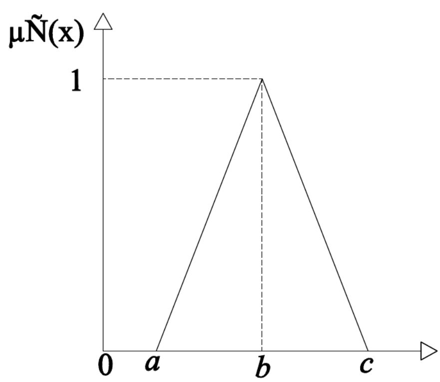


Figure 3. Representation of crisp numeric values by TFNs

(Source: Author(s) own elaboration; Created by Autocad 2007)

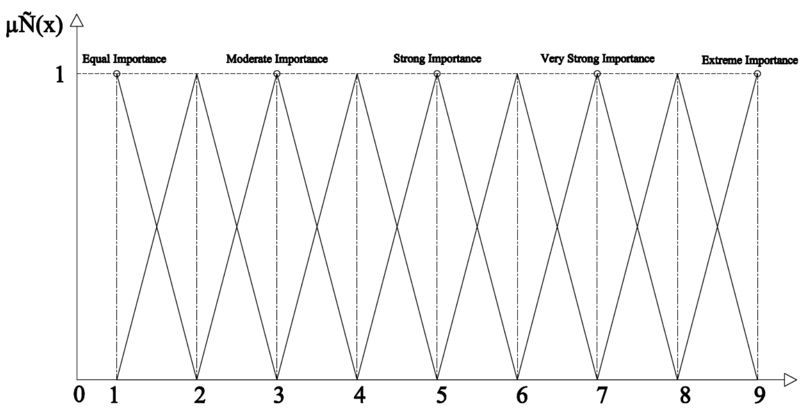


Table 5. Saaty's scale and conversion of qualitative terms into quantitative values

Mode of Importance	Saaty's Scale	Triangular Fuzzy Number (TFN)	Qualitative Terms	Quantitative Values	TFNs
Equal importance	1	(1, 1, 2)	Very high (VH)	9	(8, 9, 9)
Slight importance	3	(2, 3, 4)	High (H)	8	(7, 8, 9)
Moderate importance	5	(4, 5, 6)	Above average (AA)	7	(6, 7, 8)
Strong importance	7	(6, 7, 8)	Average (A)	5	(4, 5, 6)
Extreme importance	9	(8, 9, 9)	Below average (BA)	3	(2, 3, 4)
Intermediate values	2	(1, 2, 3)	Low (L)	2	(1, 2, 3)
	4	(3, 4, 5)	Very low (VL)	1	(1, 1, 2)
	6	(5, 6, 7)			
	8	(7, 8, 9)			

Source: Author(s) own elaboration; Saaty (1980)

$$\widetilde{N}_1 - \widetilde{N}_2 = (a_1 - a_2, b_1 - b_2, c_1 - c_2) \tag{3}$$

$$\widetilde{N}_1 \times \widetilde{N}_2 = (a_1 \times a_2, b_1 \times b_2, c_1 \times c_2) \tag{4}$$

$$\widetilde{N}_1 / \widetilde{N}_2 = (a_1 / a_2, b_1 / b_2, c_1 / c_2) \tag{5}$$

$$\lambda \widetilde{N}_1 = (\lambda a_1, \lambda b_1, \lambda c_1) \tag{6}$$

$$\widetilde{N_1^{-1}} = (\frac{1}{c_1}, \frac{1}{b_1}, \frac{1}{a_1}) \tag{7}$$

The aggregate of the decisions given by 'd' decision makers e.g., $\{(a_1, b_1, c_1), (a_2, b_2, c_2), (a_3, b_3, c_3)\ldots, (a_d, b_d, c_d)\}$is given by the Equation (8) (Rostamzadeh et al., 2017).

$$\bar{A}(\widetilde{N}_1, \widetilde{N}_2 \ldots, \widetilde{N}_d) = (\frac{1}{d}\sum_{i=1}^{d} a_i, \frac{1}{d}\sum_{i=1}^{d} b_i, \frac{1}{d}\sum_{i=1}^{d} c_i) \tag{8}$$

Where, $a_i > 0$, $b_i > 0$, $c_i > 0$, $d_i > 0$, $\lambda > 0$ and $i = 1,2\ldots, d$.

Before moving to the main Buckley analysis, the consistency of Table 4 need to be checked using the following steps as explained below.

The relative pair-wise comparisons among the chosen parameters presented in Table 4 follows the establishment of a matrix in the form of Equation (9).

$$B(n_i \times n_j) = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1j} \\ b_{21} & b_{22} & \cdots & b_{2j} \\ \cdots & \cdots & \cdots & \cdots \\ b_{i1} & b_{i2} & \cdots & b_{ij} \end{bmatrix} \tag{9}$$

Second step follows the normalization of matrix 'B' using Equation (10) to stabilize the performance data 'b_{ij}' of Table 4. However, 'N_{ij}^{A}' represents the normalized (or stabilized) values.

$$N_{ij}^{A} = \frac{b_{ij}}{\sum_{i=1}^{n} b_{ij}} \tag{10}$$

Eigen (or priority) vector (EV_i) of each criterion are calculated using Equation (11).

$$EV_i = \frac{\sum_{j=1}^{n} N_{ij}^{A}}{n} \tag{11}$$

Multiplying the pair-wise matrix 'B' with the EV matrix to get the consistency of each criterion designated as 'CN_i' shown by Equation (12).

$$CN \begin{bmatrix} CN_1 \\ CN_2 \\ \cdots \\ CN_i \end{bmatrix} = B \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1j} \\ b_{21} & b_{22} & \cdots & b_{2j} \\ \cdots & \cdots & \cdots & \cdots \\ b_{i1} & b_{i2} & \cdots & b_{ij} \end{bmatrix} \times EV \begin{bmatrix} EV_1 \\ EV_2 \\ \cdots \\ EV_i \end{bmatrix} \tag{12}$$

Compute the value of λ_{max} following Equation (13).

$$\lambda_{max} = \frac{\sum_{i=1}^{n} CN_i}{n} \tag{13}$$

The final step is to evaluate the CI and CR values using Equation (14) and Equation (15) that ultimately help the DM's to take proper judgement whether Table 4 is consistent or not.

$$CI = \frac{\left(\text{»}_{max} - n\right)}{\left(n - 1\right)} \tag{14}$$

$$CR = \frac{CI}{RI} \tag{15}$$

'n' represents the number of criteria and 'RI' represents the randomly generated index whose value can be obtained from Table 6 based on the number of criteria.

Now, proceeding towards the next step to determine the fuzzy geometric mean values ($\widetilde{G_i}$) of each criterion using Equation (16).

Table 6. Computation for consistency checking

Criteria	CN	Consistency Check		RI values			
PC	5.03877	**n**	5	**n**	**RI**	**n**	**RI**
LC	5.01008	λ_{max}	5.02048	1	0	6	1.24
RE	5.03877	**CI**	0.00512	2	0	7	1.32
MMI	5.00472	**RI**	1.12	3	0.58	8	1.41
PF	5.01008	**CR**	0.00457	4	0.9	9	1.45
Sum	25.10241	**Consistent**	Yes	5	1.12	10	1.49

Source: Author(s) own elaboration

$$\widetilde{G_i} = \left(\prod_{j=1}^{n} \widetilde{N_{ij}}\right)^{\frac{1}{n}} \tag{16}$$

Where, ‘ $\widetilde{G_i}$ ’ is the geometric mean value of the ith row criterion and ‘ $\widetilde{N_{ij}}$ ’ is the TFN of the ith row and jth column in Table 4. ‘n’ represents the number of criterion. In this case, n = 5. Table 7 displays the geometric mean values of the criteria.

The fuzzy weights ($\widetilde{W_i}$) of the parameters are now determined using the three steps outlined below.

To begin, compute the sum ($\tilde{S}$) of the geometric values ($\widetilde{G_i}$) of the criteria as shown in Equation (17). The calculation process is carried out according to the summation rule given by Equation (2). The sum ($\tilde{S}$) obtained is also a triangular fuzzy number.

$$\tilde{S} = \sum_{i=1}^{m} \widetilde{G_i} = (\widetilde{G_1} + \widetilde{G_2} + \widetilde{G_3} + ... + \widetilde{G_m}) \tag{17}$$

B. Secondly, using the inverse rule shown in Equation (7) to find the inverse sum.

Finally, the fuzzy criteria weights ($\widetilde{W_i}$) are computed by multiplying the inverse sum to each of the geometric value ($\widetilde{G_i}$) of the criteria as shown in Equation (18). The calculated fuzzy weights ($\widetilde{W_i}$) are shown in Table 7.

$$\widetilde{W_i} = \widetilde{G_i} \times \left(\widetilde{G_1} + \widetilde{G_2} + \widetilde{G_3} + ... + \widetilde{G_m}\right)^{-1} \tag{18}$$

Where, (i = 1, 2…, m; j = 1, 2…, n). The TFNs are defuzzified using the center of gravity method (COG) (Samanta, 2018) to transform it into non-fuzzy numbers. As indicated in Table 7, the actual criteria (w_j) weights are determined by normalizing these defuzzified values.

Table 7. Determination of criteria weights

Criteria	Fuzzy Geometric Mean Values ($\widetilde{G_i}$)	Fuzzy Weights ($\widetilde{W_i}$)	Defuzzification	Actual Weights (w_j)
PC	2.4915, 2.8094, 4.0953	0.2342, 0.3916, 0.6563	0.4273	0.38948
LC	0.4884, 0.6034, 0.9441	0.0459, 0.0841, 0.1513	0.0938	0.08550
RE	2.4915, 2.8094, 4.0953	0.2342, 0.3916, 0.6563	0.4273	0.38948
MMI	0.2805, 0.3480, 0.5610	0.0264, 0.0485, 0.0899	0.0549	0.05004
PF	0.4884, 0.6034, 0.9441	0.0459, 0.0841, 0.1513	0.0938	0.08550
Sum $\widetilde{G_i}$	6.2403, 7.1736, 10.6398	**Total**	1.0971	1
Inverse sum	$\frac{1}{10.6398}, \frac{1}{7.1736}, \frac{1}{6.2403}$			

Source: Author(s) own elaboration

COPRAS-ARAS Hybrid MCDM Model

Zavadskas et al. (2001) were the first to use the COPRAS technique to access building life cycles, which takes into account the effect of beneficial and cost criteria individually to estimate the relative effects of the alternatives. The ARAS technique, on the other hand, assessed the degree of utility of each alternative in relation to the optimal best choice (Zavadskas and Turskis, 2020). Zavadskas and Turskis (2020) created it in 2010 to assess the microclimate in office environments. In this hybrid model of COPRAS and ARAS, both these concepts are combined to reflect the benefits of these two separate MCDM tools. This method starts with the creation of an assessment (decision or evaluation) matrix ($m_i \times n_j$) using Equation (19). The proposed evaluation matrix is portrayed in Table 8.

$$E\,(m_i \times n_j) = \begin{bmatrix} e_{11} & e_{12} & e_{13} \cdots e_{1n} \\ e_{21} & e_{22} & e_{23} \cdots e_{2n} \\ e_{31} & e_{32} & e_{33} \cdots e_{3n} \\ \cdots & \cdots & \cdots \cdots \cdots \\ e_{m1} & e_{m2} & e_{m3} \cdots e_{mn} \end{bmatrix} \tag{19}$$

In this ongoing MCDM analysis, PC, LC, and RE are the objective measures, and MMI and PF are the subjective measures. The values of the three objective elements are derived from Rao's (2007) earlier article, and four decision-makers from the committee supplied their own perspectives on the remaining two subjective factors shown in Table 8. According to the scale in Table 5, the qualitative linguistic phrases for MMI and PF are transformed into their respective quantitative measurements and TFNs depicted in Table 9.

The fuzzy decisions made by the four decision-makers for the two subjective criteria, MMI and PF are aggregated using Equation (8) and presented in Table 9. Finally, the fuzzy weights of the MMI and PF parameters are again defuzzified using the COG approach to yield the crisp numeric values shown in Table 9. As a result, the final performance values of the three robot choices are produced and the ultimate decision matrix is displayed in Table 10.

In Table 10, 'Robot 0' (or RB) represents the ideal robot alternative created by taking into account the ideal values of each criterion, i.e., the least values for the minimum (non-beneficial) criteria and the highest values for the maximum (beneficial) criteria. Now, conducting the linear normalization using Equation (20) and Table 11 shows the normalized scores.

$$N_{ij} = \frac{e_{ij}}{\sum_{i=1}^{m} e_{ij}} \tag{20}$$

'e_{ij}' and 'N_{ij}' are the assessment score and normalized score of the jth criteria and ith alternatives respectively.

Table 8. Evaluation matrix

Alternatives	PC in 1000$	LC in kg	RE in mm	MMI				PF			
				DM1	DM2	DM3	DM4	DM1	DM2	DM3	DM4
RB1	73	48	0.15	A	AA	AA	H	H	AA	A	VH
RB2	71	46	0.18	AA	H	A	A	VH	H	VH	AA
RB3	75	51	0.14	BA	L	BA	VL	H	AA	H	A

(ource: Author(s) own elaboration; Rao (2007); Panel board members

Table 9. MMI and PF conversion analysis into precise numerical numbers

Alternative	Decision Maker 1		Decision Maker 2		Aggregated Fuzzy Weights	
	MMI	PF	MMI	PF	MMI	PF
RB1	5	8	7	7	5.75, 6.75, 7.75	6.25, 7.25, 8
	4,5,6	7,8,9	6,7,8	6,7,8		
RB2	7	9	8	8	5.25, 6.25, 7.25	7.25, 8.25, 8.75
	6,7,8	8,9,9	7,8,9	7,8,9		
RB3	3	8	2	7	1.5, 2.25, 3.25	6, 7, 8
	2,3,4	7,8,9	1,2,3	6,7,8		
Alternative	Decision Maker 3		Decision Maker 4		Defuzzified Weights	
	MMI	PF	MMI	PF	MMI	PF
RB1	7	5	8	9	6.75	7.16667
	6,7,8	4,5,6	7,8,9	8,9,9		
RB2	5	9	5	7	6.25	8.08334
	4,5,6	8,9,9	4,5,6	6,7,8		
RB3	3	8	1	5	2.33333	7
	2,3,4	7,8,9	1,1,2	4,5,6		

Source: Author(s) own elaboration

Table 10. Reconstructed assessment matrix

Nature of Criteria	(-)	(+)	(-)	(+)	(+)
Robot 0 (Ideal alternative) (RB)	**71**	**51**	**0.14**	**6.75**	**8.08334**
Alternatives	**PC in 1000$**	**LC in kg**	**RE in mm**	**MMI**	**PF**
RB1	73	48	0.15	6.75	7.16667
RB2	71	46	0.18	6.25	8.08334
RB3	75	51	0.14	2.33333	7

Source: Author(s) own elaboration; Rao (2007)

Table 11. Normalized matrix

Notations	w_1	w_2	w_3	w_4	w_5
Weights (w_j)	**0.38948**	**0.08550**	**0.38948**	**0.05004**	**0.08550**
Alternatives	**PC**	**LC**	**RE**	**MMI**	**PF**
RB	**0.24483**	**0.26020**	**0.22951**	**0.30566**	**0.26648**
RB1	0.25172	0.24490	0.24590	0.30566	0.23626
RB2	0.24483	0.23469	0.29508	0.28302	0.26648
RB3	0.25862	0.26020	0.22951	0.10566	0.23077

Source: Author(s) own elaboration

Now the weighted values (C_{ij}) and the relative significances (R_i) of each alternative are evaluated using Equation (21) and Equation (22), respectively, and shown in Table 12.

$$C_{ij} = N_{ij} \times w_j \tag{21}$$

$$R_i = S_{+i} + \frac{S_{-min}\sum_{i=1}^{m} S_{-i}}{S_{-i}\sum_{i=1}^{m}\left(S_{-min}/S_{-i}\right)} = S_{+i} + \frac{\sum_{i=1}^{m} S_{-i}}{S_{-i}\sum_{i=1}^{m}\left(1/S_{-i}\right)} \tag{22}$$

'w_j' represents the weight of jth criterion and 'R_i' is the relative significances of the ith alternative. 'C_{ij}' is the weighted score of the jth criteria and ith alternatives.

'S_{+i}' and 'S_{-i}' in Equation (22) reflect the addition of the weighted values of maximum and minimum criteria, which may be found using Equation (23) and Equation (24) respectively. 'S_{-min}' is the smallest of S_{-i} values.

$$S_{+i} = \sum_{j=1}^{n} C_{+ij} \rightarrow \sum_{i=1}^{m} S_{+i} = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{+ij} \tag{23}$$

$$S_{-i} = \sum_{j=1}^{n} C_{-ij} \rightarrow \sum_{i=1}^{m} S_{-i} = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{-ij} \tag{24}$$

'C_{+ij}' and 'C_{-ij}' denotes the weighted values of maximum and minimum criteria.

Finally, using Equation (25), each alternative's quantitative utility degree (QU_i) is calculated, and the ranking of the three robot alternatives is provided in Table 12.

$$QU_i = \frac{R_i}{R_0} \tag{25}$$

Where, (i = 1, 2…., m; j = 1, 2…., n). 'R_0' is the relative significances of the ideal robot alternative (RB) indicated in Table 12.

RESULTS AND VALIDATION

The robot options are ranked according to declining QU_i values, as indicated in Table 12. This section includes the comparative analysis and validation to demonstrate the accuracy and stability of the recommended methodologies.

Table 12. Ranking of robots by COPRAS-ARAS hybrid model

Alternatives	PC	LC	RE	MMI	PF	R_i	QU_i	Rank
RB	**0.09536**	**0.02225**	**0.08939**	**0.01530**	**0.02278**	**0.26513 = R_0**	-	-
RB1	0.09804	0.02094	0.09577	0.01530	0.02020	0.25165	0.94917	1
RB2	0.09536	0.02007	0.11493	0.01416	0.02278	0.23694	0.89368	3
RB3	0.10073	0.02225	0.08939	0.00529	0.01973	0.24628	0.92891	2

Source: Author(s) own elaboration

Comparative Analysis Among Various MCDM Models

The recommended ranking using COPRAS-ARAS hybrid model is compared with the other MCDM tools to check the accuracy of the proposed model. TOPSIS, MULTIMOORA, ARAS, WASPAS, MOORA, WPM, COPRAS, and WSM are eight other MCDM tools that were further used to determine the three alternative robot ranks using the same FAHP parameter weights as given in Table 13. The derived rankings from the eight distinct methodologies are compared with the hybrid model ranking in Table 14, and a comparison with Rao's (2007) previously presented rankings is also performed. Table 13 features the following expressions for different methodologies used.

S_i^+ (PIS) = Positive Ideal Solution
WP_i = Weighted product
S_i^- (NIS) = Negative Ideal Solution
J_i = Joint generalized criterion
RC_i = Relative closeness co-efficient
R_i = Relative significances
y_i = Weighted performance
U_i^{COPRAS} = Quantitative utility
$U_i^{MULTIMOORA}$ = Utility values
V_i = Optimality values
WS_i = Weighted sum
U_i^{ARAS} = Degree of utility

Table 13 displays the robot ranks achieved using various methodologies. It is clear that all of the MCDM methodologies produce the same ranking, demonstrating the robustness of the current MCDM study. All of the MCDM approaches indicated that robot 1 is the best option, whereas robot 2 is the worst. Moreover, the ranks among the applied models hold a strong Spearman rank correlation coefficient of one (SRCC = 1). Table 14 compares the current rankings obtained from various MCDM approaches with the results of previous researchers. Table 14 also specifies the final robot alternatives ranking using Borda and Copeland's voting method.

Table 13. Robot rankings using eight other MCDM algorithms

Alternatives	**TOPSIS**				**MOORA**		**MULTIMOORA**	
	S_i^+ (PIS)	**S_i^- (NIS)**	**RC_i**	**Rank**	**y_i**	**Rank**	**$U_i^{MULTIMOORA}$**	**Rank**
RB1	0.01697	0.04918	0.74344	1	-0.30668	1	1.39437	1
RB2	0.05737	0.02510	0.30437	3	-0.34192	3	1.31660	3
RB3	0.02731	0.05731	0.67724	2	-0.31991	2	1.34825	2
Alternatives	**WSM**		**WPM**			**WASPAS**		
	WS_i	**Rank**	**WP_i**		**Rank**	**J_i**		**Rank**
RB1	0.94864	1	0.94822		1	0.94843		1
RB2	0.90136	3	0.89534		3	0.89835		3
RB3	0.93503	2	0.91686		2	0.92594		2
Alternatives	**COPRAS**			**Alternatives**		**ARAS**		
	R_i	**U_i^{COPRAS}**	**Rank**			**V_i**	**U_i^{ARAS}**	**Rank**
RB1	0.34268	100	1	**Robot 0**		**0.26465 = V_0**	**-**	**-**
RB2	0.32291	94.231	3	**RB1**		0.25104	0.94857	1
RB3	0.33441	97.589	2	**RB2**		0.23802	0.89935	3
R_{max}	0.34268			**RB3**		**RB3**	0.93062	2

(Source: Author(s) own elaboration)

Table 14. Ranking comparisons of several MCDM approaches

Present Rankings				
MCDM Tools		**RB1**	**RB2**	**RB3**
COPRAS-ARAS hybrid model		1	3	2
TOPSIS		1	3	2
MOORA		1	3	2
MULTIMOORA		1	3	2
WSM		1	3	2
WPM		1	3	2
WASPAS		1	3	2
COPRAS		1	3	2
ARAS		1	3	2
Final ranking by Borda and Copeland method		1	3	2
Previously Proposed Rankings				
References	**MCDM Tools**	**RB1**	**RB2**	**RB3**
Rao [6]	GTMA	2	1	3
	WSM	2	3	1
	WPM	2	3	1
	AHP and its versions	2	3	1
	TOPSIS	2	1	3
	Modified TOPSIS	1	3	2

Source: Author(s) own elaboration; Rao (2007)

Table 14 shows that the prior rankings offered by Rao (2007) lack consistency, as the best and worst robot choices differ for different techniques. Rao (2007) found robot 2 as the best alternative to GTMA and TOPSIS methods, but the same robot 2 came out to be the worst choice by the rest of the methods. The same thing happens in the case of robot 3 as well. Robot 3 got all the first, second, and third positions at least once by different techniques. As shown in Table 14, all three robot alternatives were ranked first at least once by anyone of the MCDM tools. So, confusion still exists regarding the best and worst choices. Therefore, Rao (2007) entirely fails to meet the primary goal of identifying the best and worst robot among these three options. On the other hand, the current rankings prove its stability and consistency as all the methods suggested the same ranking order i.e., robot 1 and robot 2 are the best and the worst options respectively. There is no confusion regarding the best and worst robot choices. The research gaps that exist in the previous study by Rao (2007) are thus met. Consequently, the ranking prescribed by the hybrid model is genuine, and its output agrees with the majority of the results provided by various MCDM tools.

As a whole, the rating from the hybrid model COPRAS-ARAS is compared against eight different MCDM tools to determine whether the hybrid model is producing the correct ranking or not. It has been found in Table 14 that all the applied approaches yield the same findings, indicating that the newly constructed hybrid model is giving accurate results. Furthermore, the same output in all circumstances indicates that the overall analysis is consistent and generates a stable ranking. As we can observe from Table 14 that the previous analysis by Rao (2007) shows different rankings by different methods lead to confusion regarding the best and the worst choices since different methods pick different robot alternatives as the best and worst. This is one of the research gaps that the authors have identified and tried to establish a hybrid MCDM system capable of producing trustworthy and consistent findings.

Similarly, no such misunderstanding arises in the current research because all the adopted tools propose the same consistent ranking throughout, demonstrating the robustness of the entire study. The final preference ranking order of the robot alternatives can be sequentially placed as follows.

Robot 1 < Robot 3 < Robot 2

Sensitivity Analysis

Sensitivity analysis is used to demonstrate the consequences of changes in the input parameters provided by the MCDM models and to evaluate the model's sensitivity (Karande et al., 2016). Sensitivity analysis permits a) identification of the most volatile input factors that produce the critical performance variance., b) to examine of the decision-making model's stability and robustness, and c) to determine the range of input parameter values for which the model produces consistent results (Karande et al., 2016). Zavadskas et al. (2006) reported in their article, "the MCDM method's output is modified by two input parameters, criteria weights, and performance data". As a result, sensitivity analysis is performed to investigate the impact of different criteria weights on the final ranking. It allows decision-makers to investigate the capability of MCDM techniques in discovering the least sensitive solution, minimizing ambiguity in selection concerns, and ostensible performance trading (Karande et al., 2016). Therefore, three phases of sensitivity tests are carried out in this study to investigate the effect of varying criteria weights on the alternative ranking achieved using various MCDM approaches (Goswami et al., 2021).

Single Dimensional Weight Sensitivity Analysis

In this single-dimensional strategy, the weight fluctuates within a practical range for the most important criterion, and the weights of the remaining parameters are modified equally to meet the additional weight constraint., i.e., $\sum_{j=1}^{n} w_j = 1$. The weights ratio does not remain constant due to the non-proportional deviation of parameter weights, resulting in a distinct combination of new weights. Typically, the criterion having the highest weight value is considered the most important criterion since it has the largest influence on the alternative ranking. It is critical to identify the potential range within which the weight of the chosen criterion can be modified since this technique is based on the concept of weight additivity and parametric weights cannot be negative. Thus, the maximum allowable weight of the given parameter is limited. In this case, the weight of the most significant parameter can be maximum increased to w_j* and reduced to a minimum of 0 (Karande et al., 2016; Goswami et al., 2021). Equation (26) can be used to calculate the value of w_j*.

$$w_j^* = [w_j^{max} + (\text{n-1}) \times w_j^{min}] \tag{26}$$

In this case, there is a tie between PC and RE parameters. Both of them are acquiring the highest weightage. So, let's first consider PC as the critical parameter with the highest weightage of 0.38948. Using Equation (26), the value of w_j* is determined to be 0.58965, and the PC weights are now modified to be within a reasonable range of $0 \leq w_{PC} \leq 0.58965$ as shown in Table 15. Therefore, the highest possible value of w_{PC} is limited to 0.58965, since the lowest parameter weight i.e., MMI criterion, would be negative above that limit.

Similarly, if RE is considered to be an essential parameter, the same thing occurs. This sensitivity analysis takes into account both scenarios. Table 15 displays 14 new sets of parameter weights, and Figure 4 to Figure 12 depicts the effect on alternative rankings due to weight variation in both cases, i.e., PC and RE.

From the graph profiles depicted in Figure 4 to Figure 12, it is clear that the alternative rankings are somehow affected due to the variation of important parameters' weightage. Some tools show minor variations, while some illustrate substantial drastic changes in the rankings. Let's clear out

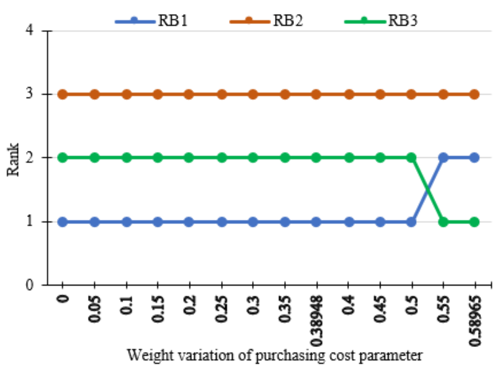
Table 15. New sets of criteria weights

	Variation of PC Parameter					Variation of RE Parameter				
	PC	LC	RE	MMI	PF	PC	LC	RE	MMI	PF
Set 1	0	0.18287	0.48685	0.14741	0.18287	0.48685	0.18287	0	0.14741	0.18287
Set 2	0.05	0.17037	0.47435	0.13491	0.17037	0.47435	0.17037	0.05	0.13491	0.17037
Set 3	0.1	0.15787	0.46185	0.12241	0.15787	0.46185	0.15787	0.1	0.12241	0.15787
Set 4	0.15	0.14537	0.44935	0.10991	0.14537	0.44935	0.14537	0.15	0.10991	0.14537
Set 5	0.2	0.13287	0.43685	0.09741	0.13287	0.43685	0.13287	0.2	0.09741	0.13287
Set 6	0.25	0.12037	0.42435	0.08491	0.12037	0.42435	0.12037	0.25	0.08491	0.12037
Set 7	0.3	0.10787	0.41185	0.07241	0.10787	0.41185	0.10787	0.3	0.07241	0.10787
Set 8	0.35	0.09537	0.39935	0.05991	0.09537	0.39935	0.09537	0.35	0.05991	0.09537
Set 9	***0.38948***	***0.08550***	***0.38948***	***0.05004***	***0.08550***	***0.38948***	***0.08550***	***0.38948***	***0.05004***	***0.08550***
Set 10	0.4	0.08287	0.38685	0.04741	0.08287	0.38685	0.08287	0.4	0.04741	0.08287
Set 11	0.45	0.07037	0.37435	0.03491	0.07037	0.37435	0.07037	0.45	0.03491	0.07037
Set 12	0.5	0.05787	0.36185	0.02241	0.05787	0.36185	0.05787	0.5	0.02241	0.05787
Set 13	0.55	0.04537	0.34935	0.00991	0.04537	0.34935	0.04537	0.55	0.00991	0.04537
Set 14	0.58965	0.03546	0.33944	0	0.03546	0.33944	0.03546	0.58965	0	0.03546

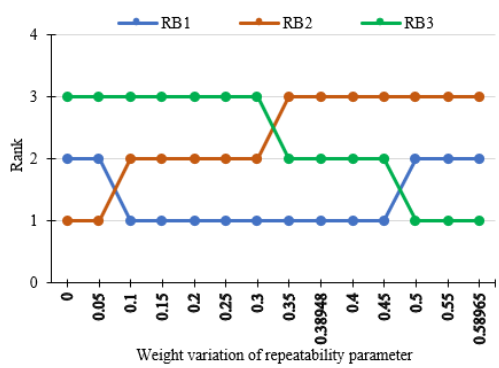
Source: Author(s) own elaboration

Figure 4. COPRAS-ARAS hybrid MCDM model

Source: Author(s) own elaboration; Created using MS Word 2010



a) Variation of PC parameter

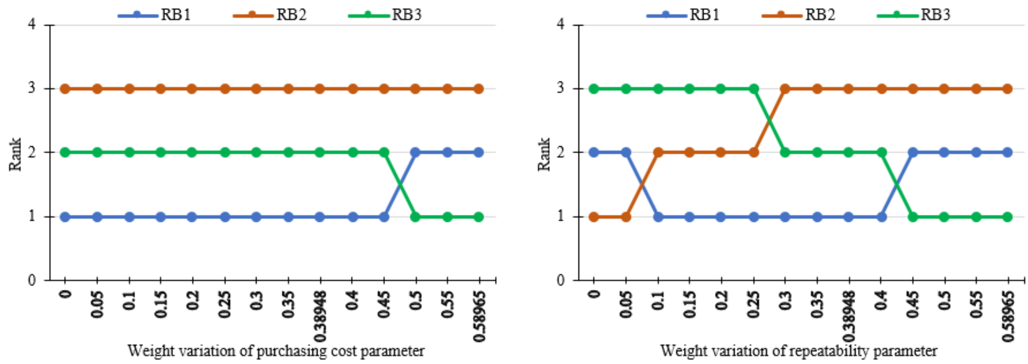


b) Variation of RE parameter

some important points one by one. To begin, if the question is raised about the essential criterion for this present decision-making problem among these two parameters, i.e., PC and RE, then the answer would be repeatability (RE). Although both the factors have the same importance (weight), i.e., 0.38948, RE is more critical than PC. There is a strong reason for making such a statement because Karande et al. (2016) stated that "the criterion with the highest weight means that it has the greatest effect on the alternative ranking to be viewed as the most important criterion". So, here, in this case, it can be noticed from the graph profiles that, on varying the weights of the RE parameter,

Figure 5. TOPSIS

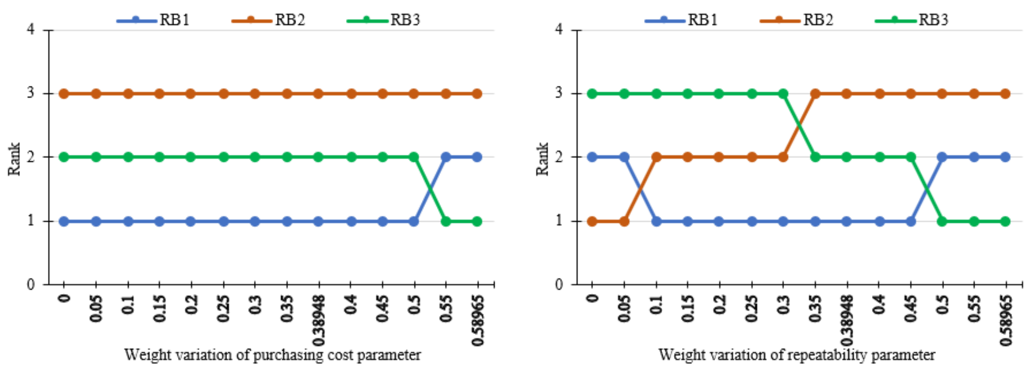
Source: Author(s) own elaboration; Created using MS Word 2010



a) Variation of PC parameter   b) Variation of RE parameter

Figure 6. MOORA

Source: Author(s) own elaboration; Created using MS Word 2010



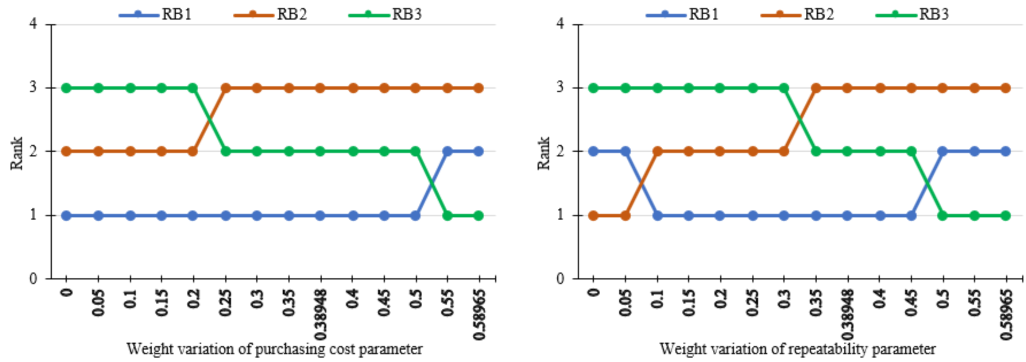
a) Variation of PC parameter   b) Variation of RE parameter

the alternative ranking shows dramatic changes in all cases for the adopted MCDM techniques than the PC parameter variation. In contrast, in PC parameter weight variation, all the tools show more stability in alternative ranking. As a result, it can be stated that repeatability has the highest impact on the alternative rating and thus can be termed as the critical parameter. At the same time, it is also true that purchasing cost (PC) is the most robust parameter than RE since its weight variation didn't significantly affect the rankings.

Secondly, let us discuss the robustness of the applied MCDM tools. The graph profiles presented in Figure 4(a) to Figure 12(a) reveal that the COPRAS-ARAS hybrid model exhibits relatively small alteration in ranks during PC parameter fluctuation, and the contour is comparable to MOORA, WSM, and ARAS, whereas, the other five tools exhibit substantial ranking variations. In the case of RE variation, all the profiles are practically the same as shown in Figure 4(b) to Figure 12(b), but the hybrid model variation is identical to WASPAS, ARAS, MULTIMOORA, COPRAS, WPM, and MOORA. As a result, it is possible to conclude that the newly constructed hybrid model is stable

Figure 7. MULTIMOORA

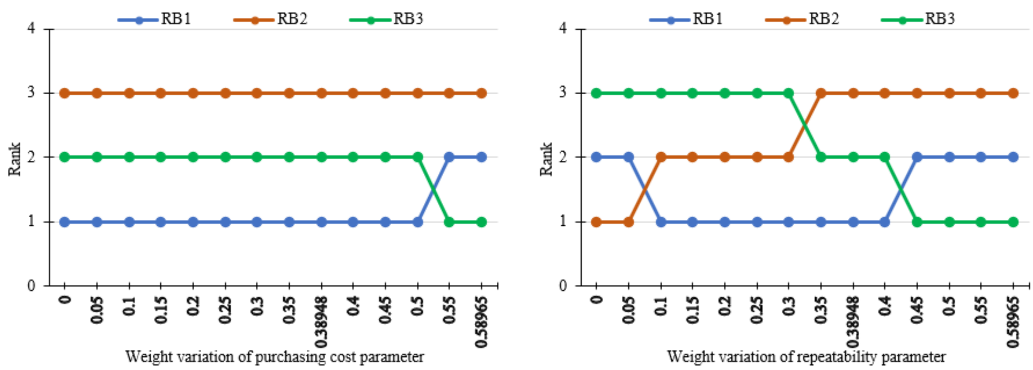
Source: Author(s) own elaboration; Created using MS Word 2010



a) Variation of PC parameter   b) Variation of RE parameter

Figure 8. WSM

Source: Author(s) own elaboration; Created using MS Word 2010

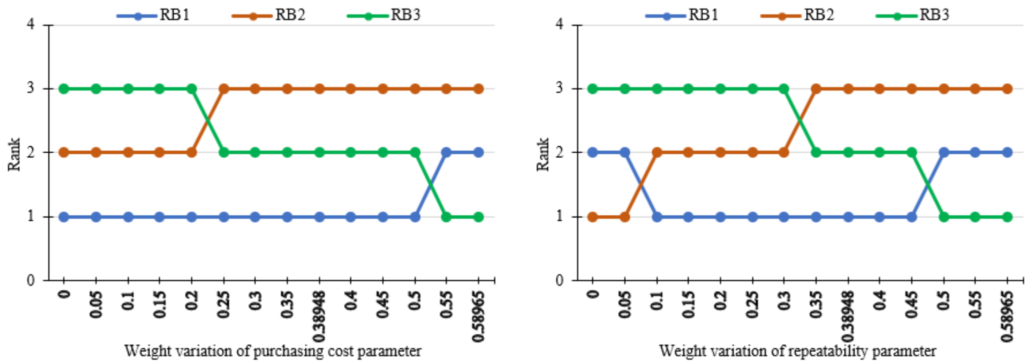


a) Variation of PC parameter   b) Variation of RE parameter

and strong enough to compete with other existing MCDM tools. Furthermore, the hybrid model also reflects equivalent characteristics as the other eight employed methodologies, which can be observed by the similar variation of graphical presentations. Before proceeding to the next point, let us first provide a brief overview of weight stability intervals. The local stability (LS) interval represents the range of weight variation over which the first-ranked alternative proposed by one method can only maintain its rank in the first position. The global stability (GS) interval, on the other hand, represents the weight range variation during which the total alternative ranking proposed by one method remains constant. Finally, the final rank-based stability (FRS) interval is the range within which the final proposed alternative ranking, i.e., RB1 – RB3 – RB2 (in this case), remains constant. Therefore, LS and GS are used to determine stability and robustness, while FRS is used to govern the efficiency and performance of the MCDM tools. In this present situation, the GS and FRS intervals are the same because the final suggested rank is the same as supplied by all of the applied MCDM methodologies.

Figure 9. WPM

Source: Author(s) own elaboration; Created using MS Word 2010

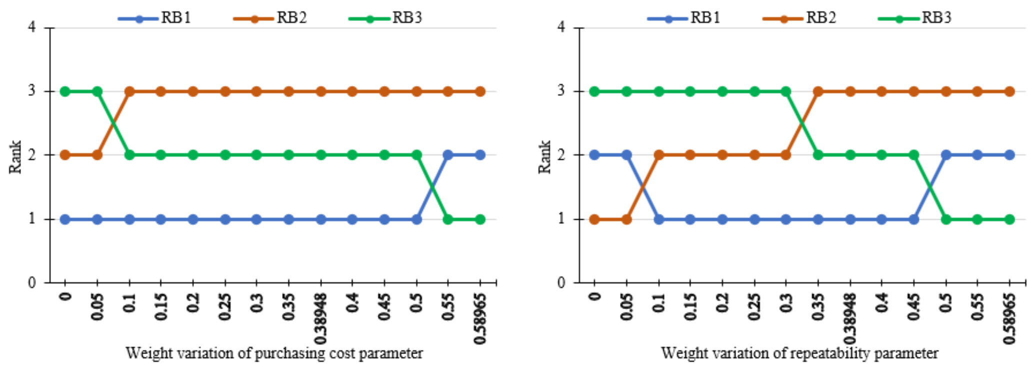


a) Variation of PC parameter

b) Variation of RE parameter

Figure 10. WASPAS

Source: Author(s) own elaboration; Created using MS Word 2010



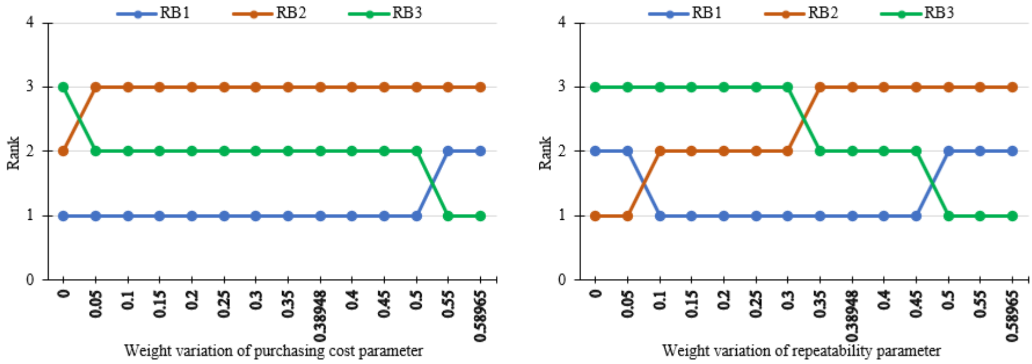
a) Variation of PC parameter

b) Variation of RE parameter

From the weight stability intervals provided in Table 16, it is observed that the hybrid model, MOORA, ARAS, TOPSIS, and WSM methods gradually lose their stability as the PC variation slowly moves towards the higher order beyond 0.45. Whereas the remaining methods particularly, WPM and MULTIMOORA, gain their stability within the intervals 0.25 and 0.5. Similarly, COPRAS and WASPAS indicate some ranking changes in the lower and upper regions, but both approaches exhibit some consistency within the interval of 0.05 to 0.5. However, when the RE parameter is varied, all of the approaches are sensitive and show a similar consistent ranking within the GS interval of 0.3 to 0.45. When comparing both LS and GS intervals during PC and RE parameter variation simultaneously, Table 16 shows that hybrid COPRAS-ARAS, MOORA, and ARAS have attained the maximum LS and GS in both scenarios, indicating that these three MCDM models are the most robust among the group. On the other hand, WPM and MULTIMOORA are the most sensitive methods in the group, with the smallest GS intervals during PC parameter variation, and WSM is the most sensitive with the smallest GS interval during RE parameter variation. Now, the most critical question is whether the main objective of this

Figure 11. COPRAS

Source: Author(s) own elaboration; Created using MS Word 2010

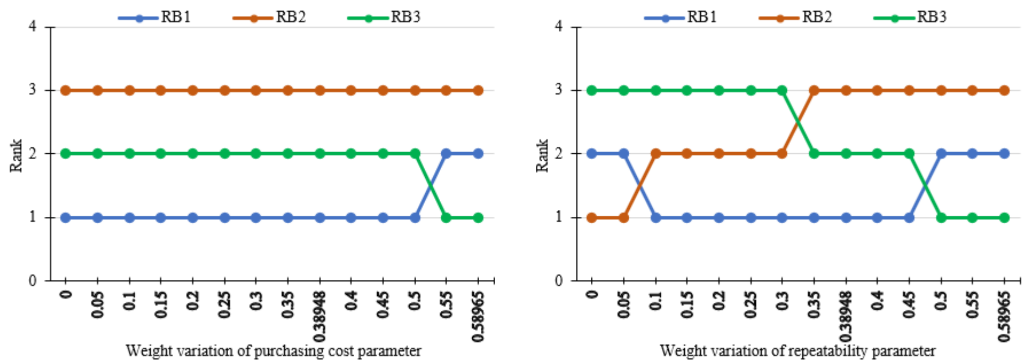


a) Variation of PC parameter

b) Variation of RE parameter

Figure 12. ARAS

Source: Author(s) own elaboration; Created using MS Word 2010



a) Variation of PC parameter

b) Variation of RE parameter

article has been met or not. Specifically, whether the newly developed hybrid model performed well? Whether it has improved the performance of the COPRAS method and met our expectations? In this context, it is worth noting that the hybrid model suggested an alternative ranking that is more stable than the solo COPRAS technique and exactly matches the other eight MCDM-assisted rankings displayed in Table 14. Table 16 shows that during PC weights variation, the hybrid model's GS and FRS intervals are more significant than COPRAS, demonstrating its good performance and stability over solo COPRAS. Still, it is also true that COPRAS's ultimate ranking is the same as others but it slightly lags behind the hybrid model and ARAS in terms of robustness. From the final ranking to the sensitivity analysis and the weight stability intervals, ARAS behaves ideally the same as the hybrid model, demonstrating that solo ARAS is also more resilient than COPRAS and other techniques. Overall, the developed hybrid model performed well in contrast to existing MCDM tools, and combining ARAS with COPRAS also increases the strength and stability of the solo COPRAS technique to some extent.

Table 16. Weight stability intervals of the applied MCDM methods

MCDM Tools	PC Parameter Variation Graphs		RE Parameter Variation Graphs	
	Local Stability (LS)	Global Stability (GS)	Local Stability (LS)	Global Stability (GS)
Hybrid COPRAS-ARAS	$0 \le w_{PC} \le 0.5$	$0 \le w_{PC} \le 0.5$	$0.1 \le w_{PC} \le 0.45$	$0.35 \le w_{PC} \le 0.45$
TOPSIS	$0 \le w_{PC} \le 0.45$	$0 \le w_{PC} \le 0.45$	$0.1 \le w_{PC} \le 0.4$	$0.3 \le w_{PC} \le 0.4$
MOORA	$0 \le w_{PC} \le 0.5$	$0 \le w_{PC} \le 0.5$	$0.1 \le w_{PC} \le 0.45$	$0.35 \le w_{PC} \le 0.45$
MULTIMOORA	$0 \le w_{PC} \le 0.5$	$0.25 \le w_{PC} \le 0.5$	$0.1 \le w_{PC} \le 0.45$	$0.35 \le w_{PC} \le 0.45$
WSM	$0 \le w_{PC} \le 0.5$	$0 \le w_{PC} \le 0.5$	$0.1 \le w_{PC} \le 0.4$	$0.35 \le w_{PC} \le 0.4$
WPM	$0 \le w_{PC} \le 0.5$	$0.25 \le w_{PC} \le 0.5$	$0.1 \le w_{PC} \le 0.45$	$0.35 \le w_{PC} \le 0.45$
WASPAS	$0 \le w_{PC} \le 0.5$	$0.1 \le w_{PC} \le 0.5$	$0.1 \le w_{PC} \le 0.45$	$0.35 \le w_{PC} \le 0.45$
COPRAS	$0 \le w_{PC} \le 0.5$	$0.05 \le w_{PC} \le 0.5$	$0.1 \le w_{PC} \le 0.45$	$0.35 \le w_{PC} \le 0.45$
ARAS	$0 \le w_{PC} \le 0.5$	$0 \le w_{PC} \le 0.5$	$0.1 \le w_{PC} \le 0.45$	$0.35 \le w_{PC} \le 0.45$
	Final Rank-Based Stability (FRS)		Final Rank-Based Stability (FRS)	
Hybrid COPRAS-ARAS	$0 \le w_{PC} \le 0.5$		$0.35 \le w_{PC} \le 0.45$	
TOPSIS	$0 \le w_{PC} \le 0.45$		$0.3 \le w_{PC} \le 0.4$	
MOORA	$0 \le w_{PC} \le 0.5$		$0.35 \le w_{PC} \le 0.45$	
MULTIMOORA	$0.25 \le w_{PC} \le 0.5$		$0.35 \le w_{PC} \le 0.45$	
WSM	$0 \le w_{PC} \le 0.5$		$0.35 \le w_{PC} \le 0.4$	
WPM	$0.25 \le w_{PC} \le 0.5$		$0.35 \le w_{PC} \le 0.45$	
WASPAS	$0.1 \le w_{PC} \le 0.5$		$0.35 \le w_{PC} \le 0.45$	
COPRAS	$0.05 \le w_{PC} \le 0.5$		$0.35 \le w_{PC} \le 0.45$	
ARAS	$0 \le w_{PC} \le 0.5$		$0.35 \le w_{PC} \le 0.45$	

Source: Author(s) own elaboration

Cost Factor Sensitivity Analysis

In this stage of sensitivity analysis, the cost element (in this case, purchasing cost) is modified over a range of values to observe the differences in rankings given by the specific model. Bhattacharya et al. (2005) developed a scientific method for combining cost-factor components with the model's overall weight scores. The subjective and objective factor measures are the two key components in this analysis, where, objective factor measure (OFM) of the alternatives are computed using Equation (27). OFM values are then used in Equation (28) to get the alternative's selection index (SI) (Bhattacharya et al., 2005).

$$OFM_i = \frac{1}{\left[PC_i \sum_{i=1}^{m} PC_i^{-1}\right]} \tag{27}$$

$$SI_i = [xSFM_i + (1\text{-}x)OFM_i] \tag{28}$$

Where, i = 1, 2…, m. The notations given in Equation (27) and Equation (28) can be defined as follows.

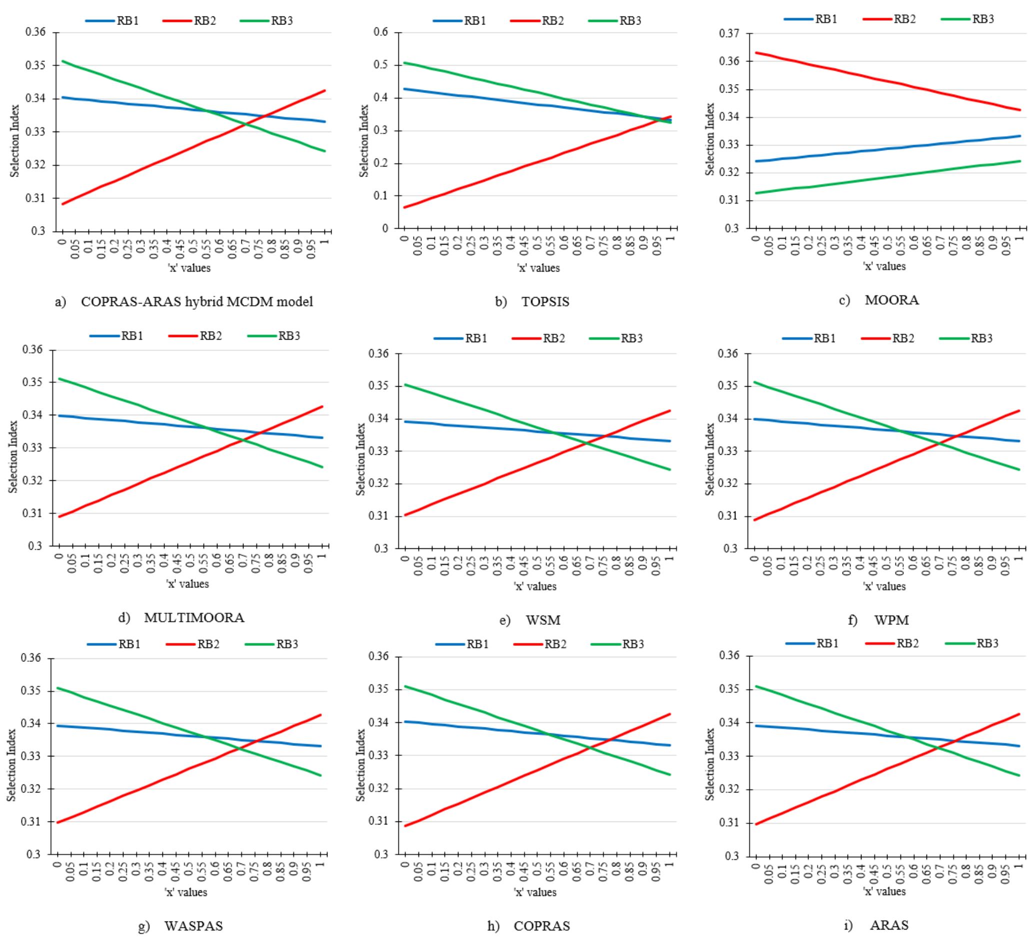
OFM_i = Objective factor measure
SI_i = Selection index
PC_i = Objective factor cost (Purchasing cost)

x = Weight of the objective decision factor
m = Number of alternatives (m = 4, in this case)
SFM_i = Subjective factor measure

Purchasing costs are taken as PC_i values provided in Table 8, whereas SFM_i are the final overall weighted score values based on which the alternative rankings are prescribed. The final scores provided in Table 12 for the hybrid model and Table 13 for the eight alternate tools should be treated as the SFM_i scores respectively. In this current situation, the objective decision weight factor 'x' values are varied within a range of $0 \leq x \leq 1$ at an interval of 0.05. The alteration in the selection index for each alternative is noted and plotted in graphical form at each point of the 'x' value to measure the sensitivity of the constructed model. This mathematical approach has been used to analyze the sensitivity of all nine accepted models and the resultant graphs for each of the MCDM tools are shown in Figure 13. For larger values of 'x', immediate consideration of the decision weight factor can considerably dominate subjective measures. Simultaneously, lower values of 'x' dominate the cost component with lower SFM_i priority values and vice versa (Bhattacharya et al., 2005).

Figure 13. Cost sensitivity analysis graphs

Source: Author(s) own elaboration; Created using MS Word 2010



Sensitivity Analysis Using Weight Replacement Strategy

In this sensitivity analysis type, the criteria weights are rearranged into the highest conceivable combinations and rankings are created for each scenario to determine the sensitivity of the applied models. The five criteria weights (w_1 w_2 w_3 w_4 w_5) can be reshuffled into 120 possible combinations following the rule $5! = 5 \times 4 \times 3 \times 2 \times 1 = 120$ highlighted in Table 17. Robot rankings were received for each of the 120 weight combinations in each model case and plotted in the form of the graph shown in Figure 14 to observe the ranking deviations.

CONCLUSION

This article aimed to investigate an industrial robot selection problem using a newly built FAHP-embedded COPRAS-ARAS hybrid MCDM system and remarkably improve the earlier proposed rankings by reducing the intricacy and ambiguity linked with the prevailing literature. At the same

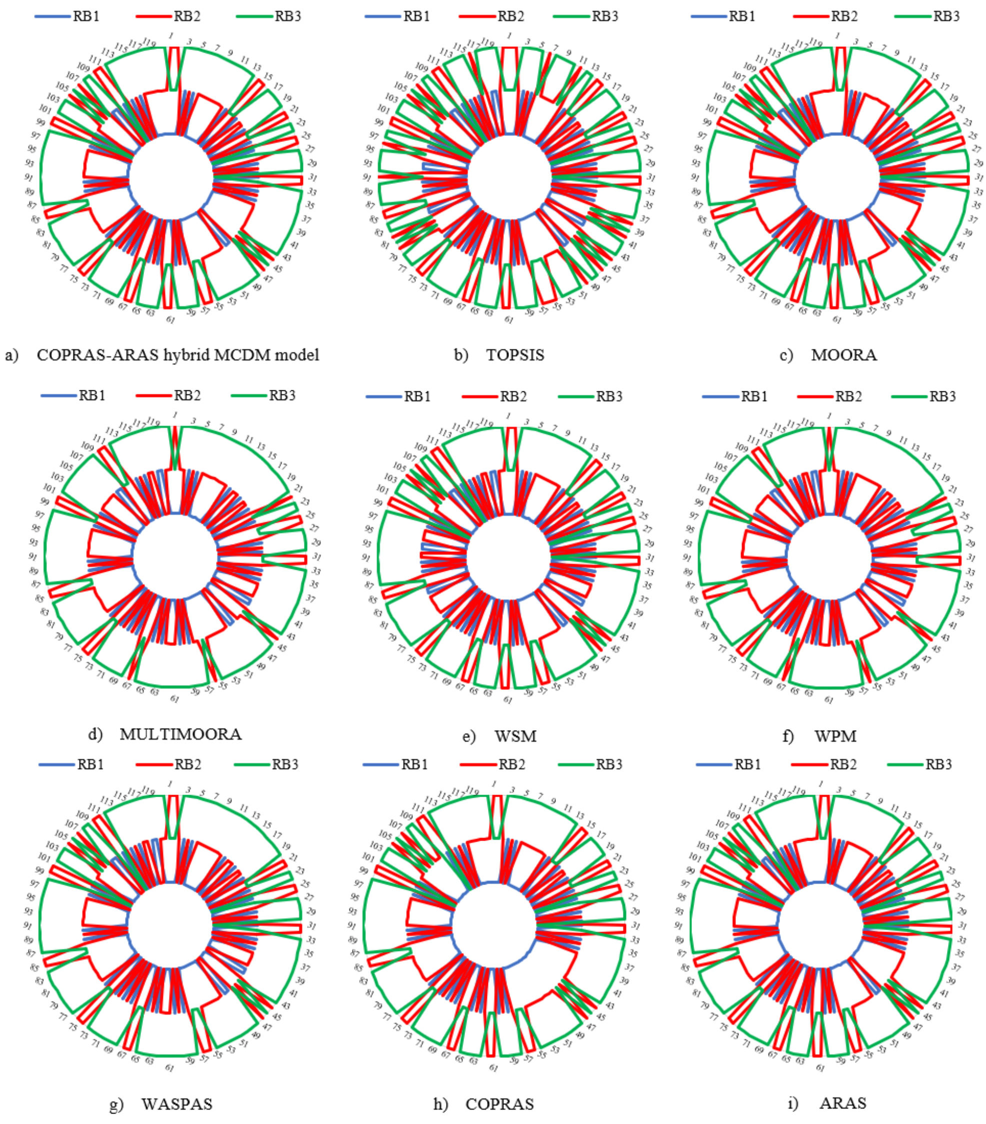
Table 17. possible combinations of five criteria weights

Sl. No.	Combinations	Sl. No.	Combinations	Sl. No.	Combinations	Sl. No.	Combinations	Sl. No.	Combinations
	Sub-Group 1		Sub-Group 2		Sub-Group 3		Sub-Group 4		Sub-Group 5
1.	$w_1w_2w_3w_4w_5$	25.	$w_2w_1w_3w_4w_5$	49.	$w_3w_1w_2w_4w_5$	73.	$w_4w_1w_2w_3w_5$	97.	$w_5w_1w_2w_3w_4$
2.	$w_1w_2w_3w_5w_4$	26.	$w_2w_1w_3w_5w_4$	50.	$w_3w_1w_2w_5w_4$	74.	$w_4w_1w_2w_5w_3$	98.	$w_5w_1w_2w_4w_3$
3.	$w_1w_2w_4w_3w_5$	27.	$w_2w_1w_4w_3w_5$	51.	$w_3w_1w_4w_1w_5$	75.	$w_4w_1w_3w_2w_5$	99.	$w_5w_1w_3w_2w_4$
4.	$w_1w_2w_4w_5w_3$	28.	$w_2w_1w_4w_5w_3$	52.	$w_3w_1w_4w_5w_1$	76.	$w_4w_1w_3w_5w_2$	100.	$w_5w_1w_3w_4w_2$
5.	$w_1w_2w_5w_3w_4$	29.	$w_2w_1w_5w_3w_4$	53.	$w_3w_1w_5w_2w_4$	77.	$w_4w_1w_5w_2w_3$	101.	$w_5w_1w_4w_2w_3$
6.	$w_1w_2w_5w_4w_3$	30.	$w_2w_1w_5w_4w_3$	54.	$w_3w_1w_5w_4w_2$	78.	$w_4w_1w_5w_3w_2$	102.	$w_5w_1w_4w_3w_2$
7.	$w_1w_3w_2w_4w_5$	31.	$w_2w_3w_1w_4w_5$	55.	$w_3w_2w_1w_4w_5$	79.	$w_4w_2w_1w_3w_5$	103.	$w_5w_2w_1w_3w_4$
8.	$w_1w_3w_2w_5w_4$	32.	$w_2w_3w_1w_5w_4$	56.	$w_3w_2w_1w_5w_4$	80.	$w_4w_2w_1w_5w_3$	104.	$w_5w_2w_1w_4w_3$
9.	$w_1w_3w_4w_2w_5$	33.	$w_2w_3w_4w_1w_5$	57.	$w_3w_2w_4w_1w_5$	81.	$w_4w_2w_3w_1w_5$	105.	$w_5w_2w_3w_1w_4$
10.	$w_1w_3w_4w_5w_2$	34.	$w_2w_3w_4w_5w_1$	58.	$w_3w_2w_4w_5w_1$	82.	$w_4w_2w_3w_5w_1$	106.	$w_5w_2w_3w_4w_1$
11.	$w_1w_3w_5w_2w_4$	35.	$w_2w_3w_5w_1w_4$	59.	$w_3w_2w_5w_1w_4$	83.	$w_4w_2w_5w_1w_3$	107.	$w_5w_2w_4w_1w_3$
12.	$w_1w_3w_5w_4w_2$	36.	$w_2w_3w_5w_4w_1$	60.	$w_3w_2w_5w_4w_1$	84.	$w_4w_2w_5w_3w_1$	108.	$w_5w_2w_4w_3w_1$
13.	$w_1w_4w_2w_3w_5$	37.	$w_2w_4w_1w_3w_5$	61.	$w_3w_4w_1w_2w_5$	85.	$w_4w_3w_1w_2w_5$	109.	$w_5w_3w_1w_2w_4$
14.	$w_1w_4w_2w_5w_3$	38.	$w_2w_4w_1w_5w_3$	62.	$w_3w_4w_1w_5w_2$	86.	$w_4w_3w_1w_5w_2$	110.	$w_5w_3w_1w_4w_2$
15.	$w_1w_4w_3w_2w_5$	39.	$w_2w_4w_3w_1w_5$	63.	$w_3w_4w_2w_1w_5$	87.	$w_4w_3w_2w_1w_5$	111.	$w_5w_3w_2w_1w_4$
16.	$w_1w_4w_3w_5w_2$	40.	$w_2w_4w_3w_5w_1$	64.	$w_3w_4w_2w_5w_1$	88.	$w_4w_3w_2w_5w_1$	112.	$w_5w_3w_2w_4w_1$
17.	$w_1w_4w_5w_2w_3$	41.	$w_2w_4w_5w_1w_3$	65.	$w_3w_4w_5w_1w_2$	89.	$w_4w_3w_5w_1w_2$	113.	$w_5w_3w_4w_1w_2$
18.	$w_1w_4w_5w_3w_2$	42.	$w_2w_4w_5w_3w_1$	66.	$w_3w_4w_5w_2w_1$	90.	$w_4w_3w_5w_2w_1$	114.	$w_5w_3w_4w_2w_1$
19.	$w_1w_5w_2w_3w_4$	43.	$w_2w_5w_1w_3w_4$	67.	$w_3w_5w_1w_2w_4$	91.	$w_4w_5w_1w_2w_3$	115.	$w_5w_4w_1w_2w_3$
20.	$w_1w_5w_2w_4w_3$	44.	$w_2w_5w_1w_4w_3$	68.	$w_3w_5w_1w_4w_2$	92.	$w_4w_5w_1w_3w_2$	116.	$w_5w_4w_1w_3w_2$
21.	$w_1w_5w_3w_2w_4$	45.	$w_2w_5w_3w_1w_4$	69.	$w_3w_5w_2w_1w_4$	93.	$w_4w_5w_2w_1w_3$	117.	$w_5w_4w_2w_1w_3$
22.	$w_1w_5w_3w_4w_2$	46.	$w_2w_5w_3w_4w_1$	70.	$w_3w_5w_2w_4w_1$	94.	$w_4w_5w_2w_3w_1$	118.	$w_5w_4w_2w_3w_1$
23.	$w_1w_5w_4w_2w_3$	47.	$w_2w_5w_4w_1w_3$	71.	$w_3w_5w_4w_1w_2$	95.	$w_4w_5w_3w_1w_2$	119.	$w_5w_4w_3w_1w_2$
24.	$w_1w_5w_4w_3w_2$	48.	$w_2w_5w_4w_3w_1$	72.	$w_3w_5w_4w_2w_1$	96.	$w_4w_5w_3w_2w_1$	120.	$w_5w_4w_3w_2w_1$

Source: Author(s) own elaboration

Figure 14. Weight replacement sensitivity analysis graphs

Source: Author(s) own elaboration; Created using MS Word 2010



time, it helps to improve the single COPRAS MCDM's performance, efficacy, and stability. Based on this fundamental analysis, it is possible to conclude that robot 1 is the best choice among these three alternatives. However, robot 3 also seems to be a formidable competitor to robot 1. Any one of them can be a good choice, but robot 1 is slightly ahead of robot 3. Robot 2 should be discarded because it is the worst option according to all of the approaches. Aside from these, the main contribution of this work and the important concluding remarks might be summarized as follows.

- The newly designed hybrid MCDM system allows for the efficient and appropriate selection of the optimal robot choice for an enterprise.

- The created hybrid model demonstrates to be an extremely effective decision-making tool, as its final ranking matches all of the other applied methods. It also eventually improves the performance of the solo COPRAS tool by demonstrating its stability and consistency, consequently, the main purpose of this investigation is achieved.
- The previously recommended rankings were unstable as noted in the results and discussion section. As a result, the new evaluation is more rigorous, and robust and provides a legitimate ranking order, vastly upgrading the previous literature.
- The hybrid MCDM method suggested here is a simple, cohesive, and systematic technique that can be simply integrated into any decision-making analysis.
- Implementing fuzzy ideas into decision-making problems can produce more reliable results while also reducing the vagueness of solo AHP tools.
- This study may provide some recommendations to the factories and manufacturing firms thinking about adopting an automated material handling system in their business. Decision-makers can utilize this hybrid technique to select a certain type of material handling equipment accurately.

Furthermore, the alternative ranking proposed by the COPRAS-ARAS hybrid method is entirely genuine and yields accurate results. During validation, its ranking matches with the majority of other MCDM methods, and it also demonstrates good stability and consistency during weight variation. Hence, this hybrid model can solve different decision-making problems in various fields. As a result, this newly developed hybrid model can make significant contributions to the field of decision-making.

Limitations

The ongoing research is based on approximation and quantitative calculations. This study does not ensure that no other robots in the market are superior to the recommended one, rather, it merely shows that Robot 1 is the best option among the three options studied for this analysis. This article simply covers one general notion and attempts to dispel any doubts that may occur while selecting a suitable robot. Furthermore, criteria weights have a very high significance in MCDM concern, and any alterations in weightage value can alter the performance outcomes. As a result, additional weight estimation algorithms such as CRITIC, SMART, BWM, SWARA, entropy, and others may produce different weight values, thus altering the final ranks. Assume subjective approaches such as SMART, BWM, AHP, SWARA, etc. are applied. In that instance, subjective tools may result in biased conclusions because the relative significance matrix is entirely based on DM’s judgmental views. As a result, some discrepancies and prejudice are linked with the weights generated by subjective approaches. Furthermore, the following robot selection problem is based on a small set of fundamental criteria and alternatives. Nonetheless, additional robots and factors may be examined, causing the findings to deviate (Goswami & Behera, 2021b).

Managerial Implications

Robot selection using MCDM empowers managers to make well-informed decisions, improve operational efficiency, mitigate risks, align stakeholders, and strategically position their organizations for success in the evolving landscape of automation and robotics. This article can have several managerial implications. Here are some key implications to consider.

- **Enhanced Decision-Making Process:** MCDM techniques provide a structured framework for evaluating and comparing different robots based on multiple criteria. Managers can use these methods to systematically assess and rank robots based on their performance, features, costs, and other relevant factors. This helps in making informed decisions and reduces the risk of subjective biases.
- **Improved Efficiency and Effectiveness:** MCDM allows managers to consider multiple criteria simultaneously, enabling them to identify robots that best align with their specific operational

requirements. By selecting the most suitable robot, organizations can enhance their operational efficiency, productivity, and overall performance. This leads to cost savings, increased throughput, and improved quality of outputs.

- **Optimal Resource Allocation:** Robot selection often involves assessing various factors such as cost, maintenance requirements, reliability, and compatibility with existing infrastructure. MCDM methods enable managers to prioritize these criteria based on their relative importance and make decisions accordingly. This helps in allocating resources effectively and efficiently, optimizing investments in robotics technology.
- **Risk Mitigation:** Introducing robots into operations carries certain risks, such as technical failures, compatibility issues, and disruptions to existing workflows. MCDM provides a systematic approach to assess and mitigate these risks by considering criteria related to robot reliability, compatibility, and adaptability. Managers can select robots with robust performance records and those that align well with their existing systems, reducing the likelihood of potential disruptions.
- **Stakeholder Alignment:** Involving multiple stakeholders, such as operations managers, technicians, and end-users, is crucial when selecting robots. MCDM facilitates stakeholder engagement by providing a transparent and objective evaluation process. By considering the preferences and requirements of various stakeholders, managers can foster alignment and consensus, increasing the likelihood of successful robot implementation.
- **Long-Term Strategic Planning:** Robot selection using MCDM methods encourages managers to think strategically and consider long-term implications. They can evaluate robots based on their technological capabilities, scalability, and potential for future upgrades. This enables organizations to invest in robots that not only meet their immediate needs but also align with their long-term growth strategies and technological advancements.
- **Competitive Advantage:** The careful selection of robots through MCDM can contribute to gaining a competitive edge. By choosing the most suitable robots, organizations can differentiate themselves by offering superior products or services, reducing costs, and improving customer satisfaction. This strategic advantage can help organizations stay ahead in the market and adapt to changing customer demands.

Future Scope

The succeeding arguments can be examined in the context of future research.

- Other tools for estimating weight, both subjectively and objectively like CRITIC, SWARA, MEREC, SMART, BWM, etc., can be used to analyze the criteria weights, and discrepancies in alternative rankings can be recorded.
- To improve the precision and reliability of the selection process, more robot alternatives and criteria might be evaluated.
- The same robot assortment problem can be analyzed using a variety of prospective MCDM methods e.g., CoCoSo, EDAS, PROMETHEE, PIV, CODAS, etc., and the resulting rankings can be compared to the existing results.
- Other promising and efficient MCDM methods can be combined to create some new robust hybrid models.
- Finally, this newly designed COPRAS-ARAS hybrid model can be used in a wide range of applications. It may be the financial sector, manufacturing industries, transportation, health, and education, to broaden and investigate the capabilities of this innovative hybrid model.

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