

## Article

# Analysis of a Robot Selection Problem Using Two Newly Developed Hybrid MCDM Models of TOPSIS-ARAS and COPRAS-ARAS

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**Abstract:** Traditional Multi-Criteria Decision Making (MCDM) methods have now become outdated; therefore, most researchers are focusing on more robust hybrid MCDM models that combine two or more MCDM techniques to address decision-making problems. The authors attempted to create two novel hybrid MCDM systems in this paper by integrating Additive Ratio ASsessment (ARAS) with Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Complex PROportional ASsessment (COPRAS). To demonstrate the ability and effectiveness of these two hybrid models i.e., TOPSIS-ARAS and COPRAS-ARAS were applied to solve a real-time robot selection problem with 12 alternative robots and five selection criteria, while evaluating the parametric importance using the CRiteria Importance Through Inter criteria Correlation (CRITIC) objective weighting estimation tool. The rankings of the robot alternatives gained from these two hybrid models were also compared to the obtained results from eight other solo MCDM tools. Although the rankings by the applied methods slightly differ from each other, the final outcomes from all of the adopted techniques are consistent enough to suggest that robot 12 is the best choice followed by robot 11, and robot 4 is the worst one among these 12 alternatives. Spearman Correlation Coefficient (SCC) also reveals that the proposed rankings derived from various methods have a strong ranking relationship with one another. Finally, sensitivity analysis was performed to investigate the effects of weight variation and to validate the robustness of the implemented MCDM approaches.

**Keywords:** hybrid MCDM; ARAS; COPRAS; TOPSIS; robot selection

## 1. Introduction

In the last few decades, MCDM served as an efficient tool in the field of decision making. Researchers are working on this area, in order to upgrade the MCDM techniques and to fulfil the loop holes that exist in the previous methods. Moreover, researchers have developed new innovative MCDM models to make more precise and accurate decisions. Each day, MCDM methods are gaining importance, due to their inherent ability to judge

different alternatives [1]. At the same time, traditional MCDM techniques are becoming obsolete and outdated. To analyze any complex decision-making problem [1], a single MCDM tool is not enough to make appropriate judgements. Therefore, two or more MCDM processes should merge together, to form a hybrid model, in order to make more effective decisions. The significance of a hybrid technique is that it accumulate the advantages of each MCDM tool into one model; moreover, this technique could be used to help overcome the drawbacks of one model from the other.

In contrast, if attention is paid to the significance of industrial robots, in addition to these, it is clear that manufacturing concerns primarily focus on automated-driving systems within an industry as time passes by. Automation aids us in achieving our desired goals and can perform time-consuming tasks repeatedly—without interruption. Most industries focus on improving automated-driven systems in order to increase productivity and lower production costs in today's technologically-advanced society. Additionally, managers have to make very crucial decisions in today's competitive market for their organizations, particularly in fields where technical decisions are essential, such as robot selection [2]. Each day, customers are becoming more diverse with their demands; as a result, competition is becoming more intense [2]. Manufacturing firms are, continuously, striving to meet these complex needs in order to balance customer-oriented performance metrics [2]. Therefore, managers sometimes face difficulties during proper robot selection due to the number of available alternative robots that have a wide range of performances and various technical characteristics [2].

Robots are computer-programmed automated material handling devices that are used to perform a variety of tasks, such as welding, spray painting, part assembly, loading, unloading, pick-n-place, etc. As a result, efficient and well-organized handling systems are required to increase system flexibility and production, improve material flow efficiency, improve facility utilization, reduce lead time, as well as manage handling and labor costs [3]. Improper industrial robot selection not only reduces productivity, but also has a negative impact on the organization's reputation [4]. Therefore, proper robot selection is critical in order to increase production rate with the highest precision and accuracy. There are numerous conflicting subjective and objective criteria that can influence the appropriate robot selection decisions [4]. Despite the high initial investment, implementing robots in industries has numerous advantages. For example, industrial robots can perform repetitive, complex, and dangerous tasks with precision, and they can also significantly increase the efficiency and productivity of manufacturing organizations. Bhangale et al. [5] stated that “over 75 important attributes must be considered when selecting a robot for a specific industrial application”. Among these attributes, Athawale and Chakraborty [6] identified some of the critical factors to consider when selecting a suitable robot alternative, such as load carrying capacity, repeatability, accuracy, speed, durability, cost, man-machine interface, manipulator distance, accuracy, etc. Load capacity refers to how much weight (load) a robot can pick up; repeatability refers to how well a robot can return to a programmed location; accuracy refers to how closely a robot can achieve a recommended point; and speed refers to how quickly a robot can position its actuator [4]. As a result, decision makers are having difficulty deciding the most appropriate robot alternative due to the involvement of a large number of competing robot performance characteristics, and the MCDM system is the only solution to these types of contradictory problems [6].

Because of the aforementioned benefits of robots, there is an immediate need to solve this selection problem and recommend the best robot alternative to incorporate within an industry, so that manufacturing firms can obtain simple ideas before investing in the installation of automated machinery and, parallelly, the development of some novel hybrid MCDM systems are also required to execute any decision-making processes in a smooth and effective manner. The authors were motivated and convinced by these stated reasons and felt bound to create two hybrid MCDM models, implementing them in executing an industrial robot selection problem in this single research article. While carrying out a robot selection process, the decision maker (DM) must consider various qualitative and

quantitative criteria, either maximizing (beneficial) or minimizing (non-beneficial) [7]. As a result, MCDM tools are the best solutions to these types of problems with a variety of conflicting criteria. This research article presents an example of a robot selection MCDM problem and evaluates it using two newly developed TOPSIS-ARAS and COPRAS-ARAS hybrid MCDM methodologies [8]. The current robot selection problem has been solved previously by several researchers using various MCDM techniques [1,4], but the authors of this paper find all of those analyses to be contradictory and inconsistent, leaving more room to expand it by using other potential MCDM methods, and comparing the results with the previous ones.

#### *Merits and Demerits of the Adopted MCDM Approaches*

The authors took initiative in this current research work to combine ARAS [9] with COPRAS [10] and TOPSIS [11–13] due to their distinct qualities (clearly explained in the later section), and simultaneously attempted to overcome the drawbacks of these three methods. There are numerous flaws associated with these MCDM tools. The main disadvantage of the ARAS method is that it can only use maximizing attributes. The minimizing (non-beneficial) criteria must first be converted into maximizing (beneficial) factors before being used [14]. As a consequence, the ARAS method may produce contradictory outcomes [14]. In addition, ARAS is a sensitive tool, and even minor changes in the data can have an impact on the results. This sensitive property of the ARAS method is also demonstrated during the sensitivity analysis in this present article. On the other hand, the devoted ranks obtained by COPRAS may differ from those obtained by other methods [15]. As a result, this is one of the drawbacks of the COPRAS technique.

COPRAS MCDM, despite having some flaws, has a plethora of strong positive characteristics that more than compensate for those minor flaws. First, one of the most significant advantages of COPRAS is its ability to treat beneficial and non-beneficial parameters separately, which thankfully correct a shortcoming in the ARAS method [14]. Furthermore, in terms of parameter weight variation, COPRAS is more robust and stable than ARAS. These explanations support the conclusion that COPRAS is a more effective and superior tool than ARAS in general. Being an inferior tool, the disadvantages of ARAS are also more severe than those of COPRAS and needs to be managed properly. Hence, it is a “high time” for the researchers to take action to improve the performance of ARAS. Thus, on merging these two tools, and incorporating some of the significant advantages and qualities of both COPRAS and ARAS, some of the weaknesses can be abolished. As a result, the current hybrid model was developed to address some of these shortcomings, and it can produce more relevant results than these solo methods. More specifically, by incorporating COPRAS alongside it, the performance and stability of the ARAS MCDM can be deliberately improved.

When it comes to the TOPSIS technique, it also has some merits and demerits. According to Kraujaliene [15], the TOPSIS method has two major drawbacks, which are as follows: (A) the use of Euclidean distance does not consider the correlation of the attributes [15]. (B) It is difficult to weigh and maintain consistency of judgment in this tool, especially with additional attributes [15]. However, the TOPSIS method has many potential advantages and shares some common characteristics with COPRAS:

- Regarding varying input data, TOPSIS provides the possibility of the most stable performance results than ARAS.
- The conversion of non-beneficial attributes is not required before normalization, as TOPSIS can treat maximum and minimum criteria separately, like COPRAS.
- The TOPSIS method enables interpretation of an absolute evaluation of a specific alternative and its deviation magnitude is calculated by comparing the results, starting with the best and worst average alternatives.
- The TOPSIS method is simple in terms of maintaining the same number of steps regardless of the size of the problem.

- Studying the development of hypothetical worst and best objects suitable for specific tasks is worthwhile in many areas where quantitative evaluation is required.

Apart from these advantages, TOPSIS has a very clear and transparent logic and can be used for both qualitative and quantitative data [14]. It can also be used simply when the number of options and criteria are large [14,16]. Although TOPSIS requires lengthy and time-consuming calculation steps, the following advantages of the TOPSIS tool are so impressive that the authors are destined to integrate TOPSIS alongside ARAS to enhance the ranking accuracy of both TOPSIS and the ARAS tool, while also attempting to overcome the drawbacks of one tool by another.

In addition to the various available MCDM techniques, the authors of this paper combined TOPSIS, COPRAS, and ARAS due to their significant advantages over other MCDM tools. The merits of the TOPSIS approach have already been discussed; now we will focus on the benefits of COPRAS and ARAS. First, we will discuss COPRAS MCDM. COPRAS is used to rate alternatives based on a variety of parameters, including the utility degrees of the alternatives and the weights associated with the criteria [17]. The best option is determined by considering both ideal and anti-ideal solutions [17,18]. COPRAS believes that the importance and utility degree of the investigated versions are directly and proportionally dependent on a set of criteria, efficiently specifying the alternatives, as well as the criteria weights and values [17,19,20]. These working principles demonstrate that the COPRAS approach is an important MCDM technique as well as an effective decision-making tool. According to Ayrim et al. [17], COPRAS rate alternatives using a single assessment framework that considers the impacts of both the cost and benefit type criteria. One significant benefit that distinguishes COPRAS from other MCDM approaches is that it takes into account the utility degree of alternatives, which represents a percentage, the extent of which one alternative is better or worse than the other alternatives used for comparison [17,21]. This information can help the DM make a decision [22]. Furthermore, recent research indicates that COPRAS-embedded decisions are more efficient and less biased than TOPSIS and WSM decisions [17,23], and COPRAS has more stability than WSM in the presence of data variations [15]. Moreover, COPRAS has many advantages over other MCDM tools, such as PROMETHEE, DEA, VIKOR, AHP, ELECTRE, etc., e.g., a very simple and transparent MCDM method requires much less computational time, and a high probability of graphical interpretation [17,18].

ARAS, on the other hand, is a type of MCDM tool that does not require any complex calculation steps and is responsible for the ranking of a limited number of decision alternatives, each of which must be considered concurrently in terms of the various decision criteria [9]. The main advantage of using the ARAS approach is that the degree of the alternative utility is calculated by comparing the variant to the (ideally) best one, which effectively aids in the prioritization of alternatives. As a result, when this approach is used, evaluating and ranking the alternatives is extremely convenient [9]. Moreover, Zavadskas and Turskis [9] also stated that “When attempt is taken to rank various alternatives and find ways to improve alternative projects, the ratio with an ideal alternative concept can be used”. It is clear from the preceding scenario that each MCDM technique has its own set of advantages and disadvantages. It is also true that the drawbacks of one MCDM tool can be overcome by another method based on the concept of combining two or more approaches together, and at the same time, the hybrid model accumulates the benefits of the individual tools and results in producing a more efficient decision-making model. Despite having many limitations, the authors of this paper considered the given reasons to be so strong and motivating that they were compelled to combine TOPSIS, COPRAS, and ARAS rather than other MCDM tools. The author of this article believes that the developed hybrid model would be much stronger and more robust due to the accumulation of the advantages and significant properties of these three MCDM tools. The beneficial properties of TOPSIS, COPRAS, and ARAS are considered and incorporated in the following two hybrid models of TOPSIS-ARAS and COPRAS-ARAS, resulting in forming an effective, well-organized,

and competent MCDM system. Some of the benefits of these two newly developed hybrid MCDM models of TOPSIS-ARAS and COPRAS-ARAS can be described as follows.

- The concept of ideal alternatives is used to improve the ranking efficiency [9].
- One of the most important aspects of this hybrid model is that the quantitative utility degree and relative closeness coefficient are evaluated by comparing the variant to the optimally (ideally) best one, which aids in alternative prioritization.
- This hybrid model is very simple and easy, having a clear, rational, and systematic mathematical approach.
- The most important feature of this hybrid model is its ability to treat maximum and minimum criteria separately, which eliminates inconsistency, and, as a result, can produce more precise results that are free of contradictions.

The main purpose of this article is to integrate ARAS [9] with TOPSIS [11–13] and COPRAS [10], resulting in a combined TOPSIS-ARAS and COPRAS-ARAS hybrid MCDM systems. The performances of these two hybrid tools are also investigated by implementing it to solve a real-world robot selection problem, while also attempting to eliminate the weaknesses of the three solo MCDM tools in order to improve their performance and efficiency. In this research article, a real-life robot selection [1,4] MCDM problem is considered and the goal is to propose the best robot alternative among 12 alternative robots for industrial applications. To execute this process, two completely novel hybrid models combining TOPSIS-ARAS and COPRAS-ARAS were developed and the criteria weights were evaluated using the CRITIC objective weighting tool [24]. Five conflicting criteria were considered in this analysis, out of which, three are beneficial (maximum) criteria, i.e., handling coefficient (HC), load capacity (LC), and velocity (V), while the other two, i.e., repeatability (R) and cost (C) are the non-beneficial (minimum) criteria. Further, the ranking obtained from these two hybrid models are also cross-verified and validated with the help of eight other solo MCDM tools and through sensitivity analysis.

## 2. Literature Review

Before proceeding further, we will go over some basic fundamental MCDM concepts. MCDM is a decision-making tool that assists decision makers in making sound decisions and selecting the best options from a plethora of available alternatives. For example, suppose someone wants to purchase a new car. In this case, there are numerous car models from various brands available in the market. As a result, the customer may be perplexed as to which available model would be the best choice. Furthermore, buyers may have specific choices and preferences, e.g., wanting a four-seater, it should be diesel-powered, the color should be black, it should have good mileage and solid comfort, it should cost less than INR 5 (lakhs), etc. However, it is not possible to meet all of these requirements in a single model, so the buyers would have to compromise on some of the less important factors. In such cases, MCDM techniques show individuals the right path to take and assist them in resolving their confusion while making appropriate alternative choices. MCDM proves to be a very efficient tool at dealing with these types of decision-making problems having different conflicting criteria with ease and effectiveness. TOPSIS, PIV, CoCoSo, COPRAS, PROMETHEE, ARAS, etc., are some popular MCDM techniques that were developed over the last few decades.

For many years, MCDM techniques have proved its versatility by addressing different complex problems with effective solutions in various sectors including manufacturing [21,25,26], transport [27,28], health [28], finance [29], etc. Many researchers applied MCDM tools to resolve numerous decision-making problems in a wide range of fields. Since this paper deals with the industrial robot selection issue, some examples of previous successful MCDM applications in this field are discussed in this section. In recent time, several hybrid MCDM methods were developed and applied in broad areas. Some new MCDM methods are also introduced by many researchers. Some applications of different hybrid MCDM tools in various fields and few successful MCDM implementations for analyzing robot selection problems are discussed in the following literature. Chatterjee



et al. [30] used outranking and compromise methods, ELECTRE II and VIKOR, whereas, Mondal and Chakraborty [4] applied four models of DEA to identify the optimal robots. Athawale and Chakraborty [6], while solving an industrial robot selection problem, investigated the ranking performance of 10 well-known MCDM methods and concluded that GRA, TOPSIS, and WPM performed marginally better than others.

Azimi et al. [31] used the polygon area MADM method and Shahrabi [32] implemented FAHP and FTOPSIS for the selection of the most convenient robot. Khandekar and Chakraborty [33] explored a robot selection problem, considering nine criteria and seven alternative robots, using fuzzy axiomatic design. Parameshwaran et al. [34] carried out a robot selection problem using the fuzzy Delphi method to select the important objective and subjective criteria based on the decision makers' opinion, the FAHP method to find out the criteria weights and, finally, fuzzy-VIKOR or fuzzy-TOPSIS to rank the alternatives. Ghorabae [35] illustrated a robot selection problem that had eight alternatives and seven criteria using an MCDM approach based on VIKOR with interval type-2 fuzzy sets. Karande et al. [1] studied the ranking performance of six popular MCDM methods for industrial robot selection problems. Xue et al. [36] proposed an integrated linguistic MCDM approach, combining extended QUALIFLEX for evaluating robot selection problems with incomplete weight information. Yazdani et al. [37] solved a robot selection problem by implementing the MOORA and COPRAS method. Bairagi et al. [38], Kamble and Patil [39], and Sharaf [40] solved a robot selection problem using a new multiplicative MCDM model, TOPSIS, and an ellipsoid algorithm-based MCDM approach respectively. Wang et al. [41] established a decision support model combined with the entropy weighting technique that uses the cloud model and TODIM to handle robot selection problems. Zhou et al. [42] considered a case study on a mobile robot selection in the healthcare industry to show the robustness and effectiveness of the FAHP-integrated VIKOR approach. Liu et al. [43] presented a novel robot selection model by integrating the qualitative flexible multiple criteria method (QUALIFLEX) and quality function development (QFD) theory under the interval-valued Pythagorean uncertain linguistic environment.

Banerjee et al. [44] proposed a novel multiple criteria analysis approach, and Gundogdu and Kahraman [45] developed a spherical FAHP for the ranking and selection of industrial robots. Kumar and Raj [46] implemented an integrated methodology of AHP and modified GRA to select the best mobile robot for material handling. Nasrollahi et al. [47] solved a robot selection problem using the fuzzy best–worst method and PROMETHEE for criteria weight evaluation and ranking of the alternatives, respectively. Hornakova et al. [48] confirmed that mobile robots are the best equipment for material handling in an industrial setting. Rashid et al. [49] integrated the generalized interval-valued trapezoidal fuzzy best–worst method with extended TOPSIS and extended VIKOR for the selection of the optimal industrial robot, while concluding that extended TOPSIS is more stable than extended VIKOR after testing the reliability and stability of both methods through sensitivity analysis. Rashid et al. [50] developed a hybrid MCDM methodology to select the best industrial robot alternatives by combining the BWM and EDAS method, followed by sensitivity analysis, and compared to other distance-based approaches, such as VIKOR and TOPSIS.

Aside from these literature studies, TOPSIS, ARAS, and COPRAS methods have a wide range of applications in other fields for making strategic decisions. Some of the previous works involving new hybrid MCDM models, TOPSIS, COPRAS, and ARAS, as decision-making tools, are briefly described as follows. Sakthivel et al. [51] developed two hybrid models combining FAHP with PROMETHEE and GRA to propose the best car alternative. Vinodh and Jayakrishna [52] and Khatwani et al. [53] presented a hybrid MCDM approach, integrating FAHP with fuzzy-VIKOR and TOPSIS to select the best tire recycling process and an appropriate marketing channel, respectively, where, FAHP is used to identify the relative importance of the criteria. Adali and Isik [54] solved an air-conditioner selection problem using COPRAS and ARAS methods. Afful-Dadzie et al. [55] and Kundakci [56] developed a hybrid MCDM framework of FAHP-PROMETHEE and a combined MCDM approach of MACBETH and MULTIMOORA for evaluating aid programs and automobile

selection of a marble company. Ozbek and Erol [57] selected and ranked the factoring companies with the help of COPRAS and ARAS methods. Valipour et al. [58] and Zhang et al. [59] proposed a hybrid SWARA-COPRAS framework and a hybrid combination of DEMATEL, ANP, GRA, and TOPSIS for risk assessment in a deep foundation excavation project and to select the optimal green material for sustainability.

Asodariya et al. [60] investigated a flywheel material selection problem in which the AHP and entropy methods were used to determine the subjective and objective criteria weights, respectively, and the COPRAS and TOPSIS methods were used to determine the best flywheel material alternatives. Barak and Dahooei [61] investigated the safety efficiency of airlines using a novel hybrid method involving fuzzy-DEA to calculate the criteria weights and six fuzzy-based MADM methods to rank the alternatives. Chatterjee et al. [62] performed an evaluation of green supply chain management using the grey DEMATEL-ARAS model, which was also validated with other MCDM techniques, such as grey TOPSIS-COPRAS. Kumar et al. [63] integrated AHP with TOPSIS to determine the cloud service by the most suitable candidate. Roy et al. [64] and Yang et al. [65] proposed an efficient FAHP-PROMETHEE II and DEMATEL-based ANP-VIKOR hybrid model to select the best car model and to improve the cloud service application. Zarbakhshnia et al. [66] developed a third-party reverse logistics provider selection and evaluation MADM model with risk factors, where fuzzy-SWARA is used to weight the evaluation criteria and fuzzy-COPRAS is used to rank and select the best logistics providers. Bahrami et al. [67] applied a new MCDM method involving BWM-ARAS for integrating multisource geological datasets to delineate highly Cu prospectivity areas in the Abhar area, NW Iran.

Goswami and Mitra [68] selected the best mobile model by applying AHP-ARAS and AHP-COPRAS decision-making methodology. Kumari and Mishra [69] presented the COPRAS method based on intuitionistic fuzzy sets for solving a green supplier selection problem. Ozdogan et al. [70] used FAHP and fuzzy-TOPSIS to prioritize the municipal services. Raigar et al. [71] selected an appropriate additive manufacturing process from four available alternatives using a new hybrid MCDM approach, integrating BWM to determine the criteria weights and PIV to rank the alternatives. Rani et al. [72] proposed a novel framework based on the COPRAS and SWARA approaches for evaluating and selecting the desirable sustainable supplier under the hesitant-fuzzy environment. Spyridonidou and Vagiona [73] used the GIS-based hybrid MCDM approach and Yildirim and Mercangoz [74] used FAHP and grey ARAS techniques to develop Greek offshore wind farms and evaluate the logistics performance of OECD countries. Yildizbasi and Unlu [75] made a comparison among three companies, towards industry 4.0, using FAHP and FTOPSIS. Chodha et al. [76] presented an entropy-embedded simple MCDM methodology based on TOPSIS to select an industrial robot for arc welding operations. Raffic et al. [77] conducted an experimental study on the effect of three different end milling process parameters using CRITIC for weight evaluation and TOPSIS for multi-objective optimization.

It is clear from the preceding works that, in most cases, old conventional tools, such as VIKOR, ELECTRE, PROMETHEE, etc., or other complicated MCDM systems, are frequently used to determine the best robot alternatives. Traditional MCDM tools are typically time-consuming, intricate, and involve complex mathematical calculations. As a result, an easy and simple integrated MCDM system is urgently required that can produce fair and reasonable results in a short computation period. Despite the fact that TOPSIS, COPRAS, and ARAS are one of the widely-used popular MCDM tools in the field of decision-making, but there are very few documented research works recorded on the robot selection problem that utilizes these three methods together for the assessment of robot alternatives. Additionally, the hybrid MCDM concept is still uncommon among the researchers and remains mostly unexplored. Few hybrid models have been developed in recent years, but those models are either very difficult to understand or not at all user-friendly. Even researchers have never attempted before to combine those simple and widely-used MCDM tools, such as TOPSIS, COPRAS, and ARAS. Moreover, subjective weighting tools, such as AHP, BWM, etc., are mostly used to estimate the criteria weights that can lead to

biased results, as well as inconsistencies. It is evident from the literature that CRITIC and other objective weighting tools are rarely used in the decision-making fields to evaluate the parametric weightages. As a consequence, the authors of this paper chose TOPSIS, COPRAS, and ARAS due to their significant advantages and initiates, to develop an easy and systematic CRITIC, integrating two hybrid systems, TOPSIS-ARAS and COPRAS-ARAS, to execute this robot selection issue, in order to produce unbiased and independent output results.

#### *Novelty of the Present Article*

From the literature discussed above, TOPSIS, COPRAS, and ARAS are underutilized MCDM methods in regard to exploring industrial robot selection problems, and ARAS, as a newly developed method, should be exploited more in the field of decision making. Previous researchers have conducted extensive research on robot selection using various MCDM approaches, primarily complex and time-consuming old traditional tools, such as PROMETHEE, VIKOR, ELECTRE, etc., but still, there is a need to use an easy, clear, and systematic mathematical approach to guide the decision maker in making effective industrial robot selection decisions for a specific engineering application. Until now, these MCDM methods had few applications in the engineering domain, particularly in robot selection fields. As a result, there is a huge opportunity to utilize these three MCDM tools and demonstrate their effectiveness in solving robot selection decision-making problems. Moreover, none of the researchers have ever tried before to merge TOPSIS, COPRAS, and ARAS, to develop robust hybrid MCDM systems. Hence, this article serves two purposes. One is to establish two new hybrid models by combining ARAS with TOPSIS and COPRAS, due to their distinct advantages over other MCDM methods, and the other is to solve a robot selection problem utilizing these two hybrid models, along with eight other solo MCDM methods, such as COPRAS, ARAS, WSM, WPM, WASPAS, MOORA, MULTIMOORA, and TOPSIS, by integrating CRITIC objective weights, to validate the output results. To remove the ambiguity, vagueness, and uncertainty associated with the previous analysis, this robot selection problem was again re-evaluated using different MCDM approaches, while determining the criteria weights using the CRITIC weight estimation tool. Although, this particular decision-making problem was already solved by several researchers [1,4] in the past, by implementing several MCDM techniques, the authors of this paper found all of those analyses as inconsistent and unstable, compelling the authors to again revisit and reconsider the same problem in this article. This research work intended to fill the existing loopholes and to fix the errors in the results associated with the previous experiments conducted by Mondal and Chakraborty [4] and Karande et al. [1]. Furthermore, all previous studies used the subjective weighted approach, AHP, to assess the relative importance of the criterion, which can lead to biased findings. As mentioned earlier, the AHP method deals with the pair-wise comparison matrix, which is entirely dependent on the DM's opinion, and some inconsistency is associated with the weights produced by the AHP method. On the other hand, the objective weighted method, such as CRITIC, is independent of the DM's opinion, assessment, and judgment and, therefore, yields more reliable, impartial, and unbiased criteria weights than AHP. Additionally, the CRITIC method is simple and takes less computation time than AHP, because it does not require a separate pair-wise comparison matrix to calculate the criteria weights. Therefore, CRITIC is approved in this article to evaluate the criteria weights, while the two newly developed hybrid models are used to propose the preference ranking order of the alternatives. Overall, the uniqueness of this research paper is that it solves an industrial robot selection issue for the first time, using two newly developed hybrid MCDM tools that combines TOPSIS, COPRAS, and ARAS MCDM methods, while simultaneously filling the research gaps and removing inconsistencies existing in the previous works.



### 3. Materials and Methods

The present robot selection problem is adopted from the article presented by Mondal and Chakraborty [4], where they used four models of data envelopment analysis (DEA) i.e., Banker, Charnes and Cooper (BCC), Charnes, Cooper and Rhodes (CCR), cone ratio, and additive models to sort out the most appropriate alternatives by eliminating the unsuitable ones and employing the overall weighted efficiency ranking method to propose the best robot among 12 available alternatives, while evaluating the parameter weightages using the analytic hierarchy process (AHP). The robot selection process was carried out on the basis of five conflicting criteria, out of which, three are beneficial (maximum) criteria, i.e., handling coefficient (HC), load capacity (LC), and velocity (V), while the other two, i.e., repeatability (R) and cost (C), are the non-beneficial (minimum) criteria. Later, Karande et al. [1] again reconsidered the same MCDM problem to examine the ranking performance of six popular MCDM tools utilizing the same AHP weights. The same robot selection problem is again readopted in this present article and two new hybrid MCDM models combining TOPSIS-ARAS and COPRAS-ARAS are developed to rank the robot alternatives, while the criteria weights are re-evaluated using the CRITIC weight estimation tool. To prove the ability of these two combined models, the outcome results from these hybrid techniques are also cross-verified using eight others solo MCDM tools and validated through sensitivity analysis. The steps of the applied MCDM tools and the mathematical calculations are clearly explained in the upcoming sub-sections. The flowchart model shown in Figure 1 represents the overall structure of the complete analysis.

#### 3.1. CRiteria Importance through Inter Criteria Correlation (CRITIC)

Diakoulaki et al. [24] invented the CRITIC method in 1995. It is a straightforward approach based on determining the objective weights without the involvement and intervention of any decision maker [24]. The aim of this method is to determine the objective weights of relative importance in MCDM problems [24]. The calculated weights take into account both contrast intensity and conflict, which are both present in the structure of the decision problem [24]. The developed method is based on an analytical examination of the evaluation matrix in order to extract all information contained in the evaluation criteria [24]. The procedure of the CRITIC method and the calculation of weightages are depicted by the following steps.

**Step 1:** formation of an evaluation (decision) matrix ( $m_i \times n_j$ ) having 'm' alternatives and 'n' criteria, according to Equation (1). The evaluation matrix as proposed by Mondal and Chakraborty [4] is shown in Table 1. 'e<sub>ij</sub>' is the performance score of the jth criteria and ith alternative.

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

where,  $i = 1, 2 \dots, m; j = 1, 2 \dots, n$

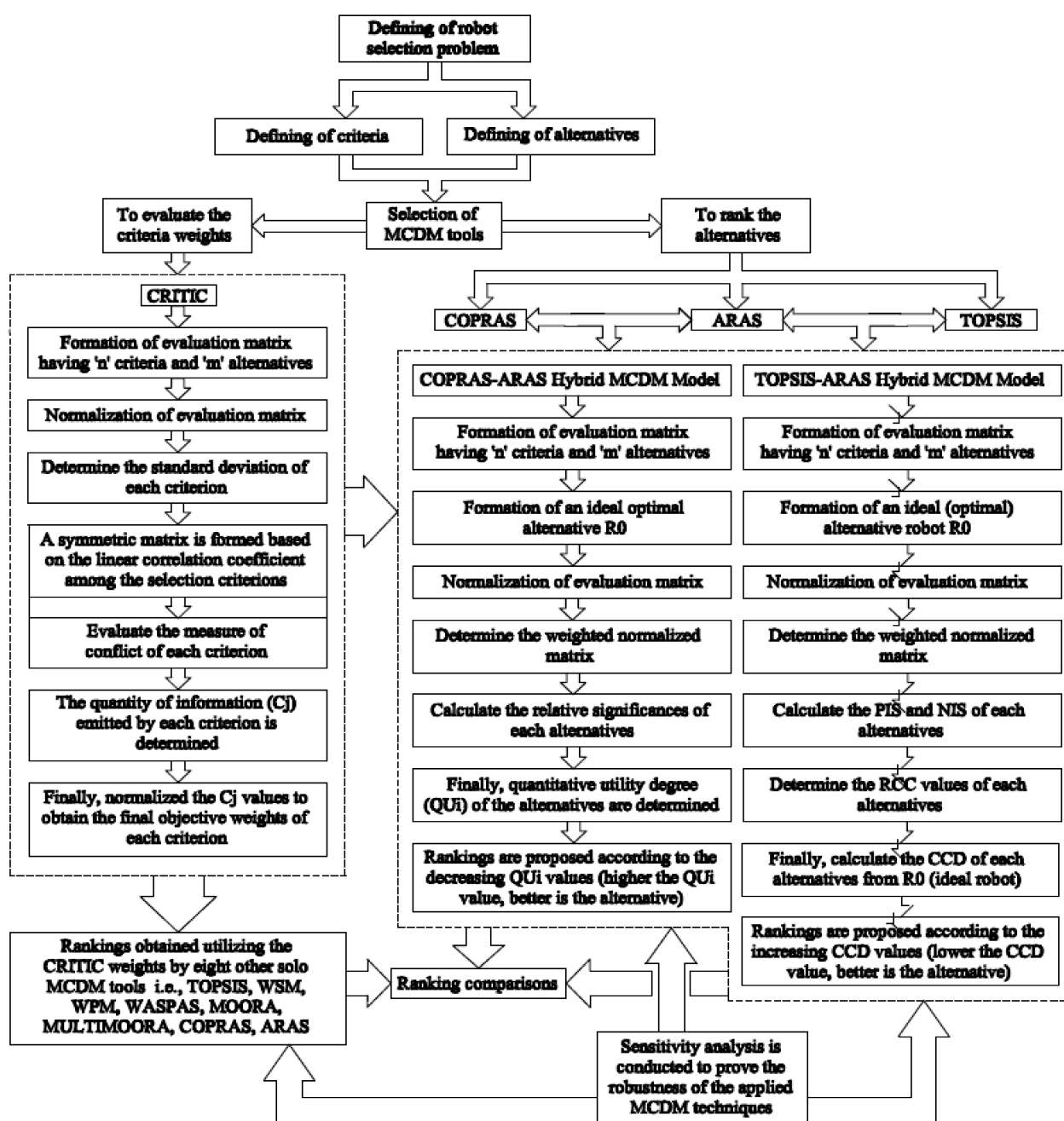


Figure 1. Flowchart model of the whole robot selection MCDM analysis. (Source: authors' own composition. Created by AutoCAD 2007).

**Table 1.** Evaluation matrix.

Nature of Criteria	Min	Min	Max	Max	Max
Alternatives	C in US\$	R in mm	HC	LC in kg	V in m/s
Robot 1	100,000	0.58824	0.995	85	3
Robot 2	75,000	0.4	0.933	45	3.6
Robot 3	56,250	0.2	0.875	18	2.2
Robot 4	28,125	0.58824	0.409	16	1.5
Robot 5	46,875	0.2	0.818	20	1.1
Robot 6	78,125	0.4	0.664	60	1.35
Robot 7	87,500	0.5	0.88	90	1.4
Robot 8	56,250	0.125	0.633	10	2.5
Robot 9	56,250	0.25	0.653	25	2.5
Robot 10	87,500	0.5	0.747	100	2.5
Robot 11	68,750	0.25	0.88	100	1.5
Robot 12	43,750	0.2	0.633	70	3
Best	28,125	0.125	0.995	100	3.6
Worst	100,000	0.58824	0.409	10	1.1

(Source: Mondal and Chakraborty, 2013; Karande et al., 2016).

**Step 2:** normalize the decision matrix in Table 1 using Equation (2). This transformation is based on the ideal point concept [24]. As a result, the values ' $N_{ij}^{(c)}$ ' below expresses how close the alternative 'i' is to the ideal value  $e_{ij}^{best}$ , which represents the best performance and far from the anti-ideal value  $e_{ij}^{worst}$ , which represents the worst performance in criterion 'j' [24]. At least one of the considered alternatives achieves both  $e_{ij}^{best}$  and  $e_{ij}^{worst}$  [24]. Table 2 shows the normalized decision matrix.

$$N_{ij}^{(c)} = \frac{e_{ij} - e_{ij}^{worst}}{e_{ij}^{best} - e_{ij}^{worst}} \quad (2)$$

where,  $i = 1, 2 \dots, m$ ;  $j = 1, 2 \dots, n$

**Table 2.** Normalized matrix for CRITIC method.

Alternatives	C	R	HC	LC	V
Robot 1	0	0	1	0.83333	0.76
Robot 2	0.34783	0.40635	0.89420	0.38889	1
Robot 3	0.60870	0.83810	0.79522	0.08889	0.44
Robot 4	1	0	0	0.06667	0.16
Robot 5	0.73913	0.83810	0.69795	0.11111	0
Robot 6	0.30435	0.40635	0.43515	0.55556	0.1
Robot 7	0.17391	0.19048	0.80375	0.88889	0.12
Robot 8	0.60870	1	0.38225	0	0.56
Robot 9	0.60870	0.73016	0.41638	0.16667	0.56
Robot 10	0.17391	0.19048	0.57679	1	0.56
Robot 11	0.43478	0.73016	0.80375	1	0.16
Robot 12	0.78261	0.83810	0.38225	0.66667	0.76
Standard deviation ( $\sigma_j$ )	0.29340	0.35747	0.28501	0.38966	0.32039

(Source: authors' own composition).

**Step 3:** determine the standard deviation ( $\sigma_j$ ) of each criterion as shown in Table 2, which quantifies the contrast intensity of the corresponding criterion [24]. As a result, the standard deviation of  $N_j^{(c)}$  is a measure of the importance of that criterion in the decision-making process [24].

**Step 4:** a symmetric matrix with dimensions ( $n_j \times n_k$ ) and a generic element ' $r_{jk}$ ' is built [24], according to Equation (3). The linear correlation coefficient between the vectors ' $N_j^{(c)}$ ' and ' $N_k^{(c)}$ ' is represented by the ' $r_{jk}$ ' element [24]. It can be seen that the lower

the value ' $r_{jk}$ ', the more discordant the scores of the alternatives in criteria ' $j$ ' and ' $k$ ' [24]. Table 3 shows the  $(5 \times 5)$  symmetric matrix. Here,  $n = 5$ .

$$S(n_j \times n_k) = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ \dots & \dots & \dots & \dots \\ r_{n1} & r_{n2} & \dots & r_{nn} \end{bmatrix} \quad (3)$$

where,  $j = 1, 2 \dots, n$ ;  $k = 1, 2 \dots, n$

**Table 3.** Symmetric matrix.

	C	R	HC	LC	V
C	1	0.44638	−0.70167	−0.70385	−0.21830
R	0.44638	1	−0.04155	−0.41928	0.00421
HC	−0.70167	−0.04155	1	0.43892	0.22969
LC	−0.70385	−0.41928	0.43892	1	0.04729
V	−0.21830	0.00421	0.22969	0.04729	1

(Source: authors' own composition).

**Step 5:** the summation in Equation (4) represents a measure of the conflict ( $M_{j,k}$ ) caused by the  $j$ th criterion in relation to the decision situation defined by the remaining criteria [24]. The measure of conflict is determined using Equation (4) and is shown in Table 4.

$$M_{j,k} = \sum_{k,j=1}^n (1 - r_{jk}) \quad (4)$$

where,  $j = 1, 2 \dots, n$ ;  $k = 1, 2 \dots, n$

**Table 4.** Measure of the conflict.

	C	R	HC	LC	V	Measure of the Conflict
C	0	0.55362	1.70167	1.70385	1.21830	5.17744
R	0.55362	0	1.04155	1.41928	0.99579	4.01024
HC	1.70167	1.04155	0	0.56108	0.77031	4.07460
LC	1.70385	1.41928	0.56108	0	0.95271	4.63691
V	1.21830	0.99579	0.77031	0.95271	0	3.93710
Measure of the conflict	5.17744	4.01024	4.07460	4.63691	3.93710	

(Source: authors' own composition).

**Step 6:** the quantity of information ( $C_j$ ) emitted by the  $j$ th criterion can be calculated by composing the measures that quantify the two concepts using the multiplicative aggregation formula shown in Equation (5) [24]. The data in MCDM problems are related to both the contrast intensity and the conflict of the decision criteria [24]. The amount of information ( $C_j$ ) by each criterion is portrayed in Table 5.

$$C_j = \sigma_j \times \sum_{k,j=1}^n (1 - r_{jk}) \quad (5)$$

where,  $j = 1, 2 \dots, n$ ;  $k = 1, 2 \dots, n$ .



**Table 5.** Final criteria weightages.

Criteria	Standard Deviation ( $\sigma_j$ )	Measure of the Conflict	$C_j$	Weights ( $w_j$ )	%
C	0.29340	5.17744	1.51906	0.21150	21.150
R	0.35747	4.01024	1.43356	0.19960	19.960
HC	0.28501	4.07460	1.16130	0.16169	16.169
LC	0.38966	4.63691	1.80680	0.25157	25.157
V	0.32039	3.93710	1.26142	0.17563	17.563
		<b>Sum</b>	7.18213		100

(Source: authors' own composition).

**Step 7:** finally, according to Equation (6), objective weights ( $w_j$ ) are computed by normalizing these ' $C_j$ ' values to unity [24]. The greater the value of ' $C_j$ ', the more information the corresponding criterion transmits and the greater its relative importance in the decision-making process [24]. The final objective criteria weightages are displayed in Table 5.

$$w_j = \frac{C_j}{\sum_{j=1}^n C_j} \quad (6)$$

where,  $j = 1, 2 \dots, n$

### 3.2. TOPSIS-ARAS Hybrid MCDM Model

The traditional TOPSIS method was first developed by Hwang and Yoon [11] in 1981, which was further extended by Yoon [12] in 1987 and Hwang et al. [13] in 1993. On the other hand, ARAS is a new MCDM method developed by Zavadskas and Turskis [9] in 2010. TOPSIS method [11–13] is based on the principle that the best alternative should have the longest distance from the negative ideal solution (NIS) and shortest distance from the positive ideal solution (PIS) [78], whereas the ARAS method measures the degree of utility of each alternative from the ideal best choice [9]. These two concepts are combined to form a new hybrid TOPSIS-ARAS model. The TOPSIS-ARAS hybrid methodology is illustrated step-wise as follows.

**Step 1:** this method begins with the creation of an evaluation (decision) matrix ( $m_i \times n_j$ ), already depicted in Table 1. Before proceeding with the normalization process, an ideal robot alternative 'Robot 0' is formed (Table 6) by taking the best values of each criterion into account, i.e., lower (minimum) values for the non-beneficial (cost) criterion and higher (maximum) values for the beneficial criterion. Table 6 clearly displays the nature of criteria and ideal alternative 'Robot 0'.

**Step 2:** Table 6 is normalized using Equation (7). In this method, vector normalization is conducted; Table 7 shows the normalized matrix

$$N_{ij(ta)} = \frac{e_{ij}}{\sqrt{\sum_{i=1}^m e_{ij}^2}} \quad (7)$$

where,  $i = 1, 2 \dots, m; j = 1, 2 \dots, n$

**Table 6.** Customized evaluation matrix for TOPSIS-ARAS and COPRAS-ARAS hybrid models.

Nature of Criteria	Min	Min	Max	Max	Max
Alternatives	C in US\$	R in mm	HC	LC in kg	V in m/s
<b>Robot 0</b>	28,125	0.125	0.995	100	3.6
<b>Robot 1</b>	100,000	0.58824	0.995	85	3
<b>Robot 2</b>	75,000	0.4	0.933	45	3.6
<b>Robot 3</b>	56,250	0.2	0.875	18	2.2
<b>Robot 4</b>	28,125	0.58824	0.409	16	1.5

Table 6. Cont.

Nature of Criteria	Min	Min	Max	Max	Max
Alternatives	C in US\$	R in mm	HC	LC in kg	V in m/s
Robot 5	46,875	0.2	0.818	20	1.1
Robot 6	78,125	0.4	0.664	60	1.35
Robot 7	87,500	0.5	0.88	90	1.4
Robot 8	56,250	0.125	0.633	10	2.5
Robot 9	56,250	0.25	0.653	25	2.5
Robot 10	87,500	0.5	0.747	100	2.5
Robot 11	68,750	0.25	0.88	100	1.5
Robot 12	43,750	0.2	0.633	70	3
Square sum	56,953,125,000	1.78829	8.22806	57555	77.00250
Square root	238,648.53865	1.33727	2.86846	239.90623	8.77511
Sum	812,500	4.32647	10.115	739	29.75

(Source: Mondal and Chakraborty, 2013; Karande et al., 2016).

Table 7. Normalized matrix for TOPSIS-ARAS hybrid model.

Weights ( $w_j$ )	0.21150	0.19960	0.16169	0.25157	0.17563
Alternatives	C	R	HC	LC	V
Robot 0	0.11785	0.09347	0.34688	0.41683	0.41025
Robot 1	0.41903	0.43988	0.34688	0.35431	0.34188
Robot 2	0.31427	0.29912	0.32526	0.18757	0.41025
Robot 3	0.23570	0.14956	0.30504	0.07503	0.25071
Robot 4	0.11785	0.43988	0.14259	0.06669	0.17094
Robot 5	0.19642	0.14956	0.28517	0.08337	0.12535
Robot 6	0.32736	0.29912	0.23148	0.25010	0.15384
Robot 7	0.36665	0.37390	0.30678	0.37515	0.15954
Robot 8	0.23570	0.09347	0.22068	0.04168	0.28490
Robot 9	0.23570	0.18695	0.22765	0.10421	0.28490
Robot 10	0.36665	0.37390	0.26042	0.41683	0.28490
Robot 11	0.28808	0.18695	0.30678	0.41683	0.17094
Robot 12	0.18332	0.14956	0.22068	0.29178	0.34188

(Source: authors' own composition).

**Step 3:** now the weighted values ( $D_{ij}^{(ta)}$ ) are evaluated using Equation (8) to form the weighted matrix shown in Table 8.

$$D_{ij}^{(ta)} = N_{ij}^{(ta)} \times w_j \quad (8)$$

where,  $i = 1, 2 \dots, m$ ;  $j = 1, 2 \dots, n$

' $w_j$ ' is the weight of the  $j$ th criteria. ' $D_{ij}^{(ta)}$ ' and ' $N_{ij}^{(ta)}$ ' are the weighted and the normalized values of the  $j$ th criteria and  $i$ th alternatives.

**Step 4:** now, we calculate the positive mean geometric distance (PIS) between the best condition and the target alternative using Equation (9); the negative mean geometric distance (NIS) between the worst condition and the target alternative is determined using Equation (10). PIS and NIS are denoted by ' $S_i^+$ ' and ' $S_i^-$ '.

$$S_i^+ = \sqrt{\sum_{j=1}^n (D_{ij}^{(ta)} - D_{bj}^{(ta)})^2} \quad (9)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (D_{ij}^{(ta)} - D_{wj}^{(ta)})^2} \quad (10)$$

where,  $i = 1, 2 \dots, m$ ;  $j = 1, 2 \dots, n$ . ' $D_{bj}$ ' and ' $D_{wj}$ ' are the best and worst values of the  $j$ th criteria, respectively, which are clearly indicated in Table 8.

**Table 8.** Weighted matrix for TOPSIS-ARAS hybrid model.

Alternatives	C	R	HC	LC	V
<i>Robot 0</i>	0.02493	0.01866	0.05609	0.10486	0.07205
<b>Robot 1</b>	0.08863	0.08780	0.05609	0.08913	0.06004
<b>Robot 2</b>	0.06647	0.05970	0.05259	0.04719	0.07205
<b>Robot 3</b>	0.04985	0.02985	0.04932	0.01888	0.04403
<b>Robot 4</b>	0.02493	0.08780	0.02306	0.01678	0.03002
<b>Robot 5</b>	0.04154	0.02985	0.04611	0.02097	0.02202
<b>Robot 6</b>	0.06924	0.05970	0.03743	0.06292	0.02702
<b>Robot 7</b>	0.07755	0.07463	0.04960	0.09438	0.02802
<b>Robot 8</b>	0.04985	0.01866	0.03568	0.01049	0.05004
<b>Robot 9</b>	0.04985	0.03731	0.03681	0.02622	0.05004
<b>Robot 10</b>	0.07755	0.07463	0.04211	0.10486	0.05004
<b>Robot 11</b>	0.06093	0.03731	0.04960	0.10486	0.03002
<b>Robot 12</b>	0.03877	0.02985	0.03568	0.07340	0.06004
<b>Best (<math>D_{bj}</math>)</b>	0.02493	0.01866	0.05609	0.10486	0.07205
<b>Worst (<math>D_{wj}</math>)</b>	0.08863	0.08780	0.02306	0.01049	0.02202

(Source: authors' own composition).

**Step 5:** we determine the relative closeness coefficient ( $RCC_i$ ) of each alternative using Equation (11). The positive and the negative distances of the alternatives, along with the closeness coefficient values, are depicted in Table 9.

$$RCC_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (11)$$

where,  $i = 1, 2, \dots, m$

The value of  $RCC$  ranges from  $0 \leq RCC_i \leq 1$ . If  $RCC_i = 1$ , then the alternative has the best condition, and if  $RCC_i = 0$ , then the alternative has the worst condition.

**Step 6:** relative closeness coefficient of the ideal alternative will always be equal to 1. Finally, we compute the closeness coefficient distances ( $CCD_i$ ) of each alternative from the ideal alternative using Equation (12). The smallest the closeness coefficient distance from the ideal alternative, the better the alternative. Table 9 shows the distances of the 12 alternatives from the ideal robot variant Robot 0.

$$CCD_i = (RCC_i^{(ideal)} - RCC_i) \quad (12)$$

where,  $i = 1, 2, \dots, m$

**Table 9.** Closeness coefficient distances of the robot alternatives.

Alternatives	S+	S−	$RCC_i$	$CCD_i$	%
<i>Robot 0</i>	0	0.14608	$1 = RCC_i^{(ideal)}$	-	-
<b>Robot 1</b>	0.09607	0.09339	0.49293	0.50707	50.707
<b>Robot 2</b>	0.08215	0.07748	0.48537	0.51463	51.463
<b>Robot 3</b>	0.09472	0.07814	0.45206	0.54794	54.794
<b>Robot 4</b>	0.12409	0.06451	0.34205	0.65795	65.795
<b>Robot 5</b>	0.10021	0.07884	0.44033	0.55967	55.967
<b>Robot 6</b>	0.08823	0.06439	0.42190	0.57810	57.810
<b>Robot 7</b>	0.08940	0.08986	0.50127	0.49873	49.873
<b>Robot 8</b>	0.10212	0.08502	0.45431	0.54569	54.569
<b>Robot 9</b>	0.08950	0.07262	0.44793	0.55207	55.207
<b>Robot 10</b>	0.08113	0.10174	0.55635	0.44365	44.365
<b>Robot 11</b>	0.05876	0.11398	0.65983	0.34017	34.017
<b>Robot 12</b>	0.04321	0.10680	0.71195	0.28805	28.805

(Source: authors' own composition).

### 3.3. COPRAS-ARAS Hybrid MCDM Model

The COPRAS method was first implemented by Zavadskas et al. [10] to assess life cycles of the building and it considers the effect of beneficial and non-beneficial criteria individually to determine the relative significances and quantitative utility of the alternatives [10]. The ARAS method, on the other hand, measures the degree of utility of each alternative relative to the ideal best choice [9] and was first developed in 2010 by Zavadskas and Turskis [9] to evaluate the microclimates in office rooms. The quantitative utility and the degree of utility concept of the COPRAS and ARAS technique is united in this hybrid model to reflect the advantages of the two individual MCDM tools. The COPRAS-ARAS hybrid methodology is illustrated step-wise as follows.

**Step 1:** this method starts with an evaluation matrix (created in Table 6), followed by linear normalization using Equation (13). The normalized matrix is shown in Table 10.

$$N_{ij}^{(ca)} = \frac{e_{ij}}{\sum_{i=1}^m e_{ij}} \quad (13)$$

where,  $i = 1, 2 \dots, m; j = 1, 2 \dots, n$

**Step 2:** the weighted values ( $D_{ij}^{(ca)}$ ) and the relative significances ( $R_i$ ) of each alternative are evaluated using Equations (14) and (15), respectively, and are shown in Table 11.

$$D_{ij}^{(ca)} = N_{ij}^{(ca)} \times w_j \quad (14)$$

$$R_i = S_{+i} + \frac{S_{-min} \sum_{i=1}^m S_{-i}}{S_{-i} \sum_{i=1}^m \left( \frac{S_{-min}}{S_{-i}} \right)} = S_{+i} + \frac{\sum_{i=1}^m S_{-i}}{S_{-i} \sum_{i=1}^m \left( \frac{1}{S_{-i}} \right)} \quad (15)$$

where,  $i = 1, 2 \dots, m; j = 1, 2 \dots, n$  and ' $R_i$ ' is the relative significances of the  $i$ th alternative. In Equation (15), ' $S_{+i}$ ' and ' $S_{-i}$ ' represents the weighted value summation of the maximizing and minimizing criteria of the  $i$ th alternative, which can be determined using Equations (16) and (17), respectively. ' $S_{-min}$ ' is the minimum among the  $S_{-i}$  values.

$$S_{+i} = \sum_{j=1}^n D_{+ij}^{(ca)} \rightarrow \sum_{i=1}^m S_{+i} = \sum_{i=1}^m \sum_{j=1}^n D_{+ij}^{(ca)} \quad (16)$$

$$S_{-i} = \sum_{j=1}^n D_{-ij}^{(ca)} \rightarrow \sum_{i=1}^m S_{-i} = \sum_{i=1}^m \sum_{j=1}^n D_{-ij}^{(ca)} \quad (17)$$

where,  $i = 1, 2 \dots, m; j = 1, 2 \dots, n$ . ' $D_{+ij}^{(ca)}$ ' and ' $D_{-ij}^{(ca)}$ ' are the weighted values of the maximizing and minimizing criteria, respectively.

**Table 10.** Normalized matrix for the COPRAS-ARAS hybrid model.

Weights	0.21150	0.19960	0.16169	0.25157	0.17563
Alternatives	C	R	HC	LC	V
Robot 0	0.03462	0.02889	0.09837	0.13532	0.12101
Robot 1	0.12308	0.13596	0.09837	0.11502	0.10084
Robot 2	0.09231	0.09245	0.09224	0.06089	0.12101
Robot 3	0.06923	0.04623	0.08651	0.02436	0.07395
Robot 4	0.03462	0.13596	0.04043	0.02165	0.05042
Robot 5	0.05769	0.04623	0.08087	0.02706	0.03697
Robot 6	0.09615	0.09245	0.06565	0.08119	0.04538
Robot 7	0.10769	0.11557	0.08700	0.12179	0.04706
Robot 8	0.06923	0.02889	0.06258	0.01353	0.08403
Robot 9	0.06923	0.05778	0.06456	0.03383	0.08403
Robot 10	0.10769	0.11557	0.07385	0.13532	0.08403
Robot 11	0.08462	0.05778	0.08700	0.13532	0.05042
Robot 12	0.05385	0.04623	0.06258	0.09472	0.10084

(Source: authors' own composition).



**Step 3:** finally, quantitative utility degree ( $QU_i$ ) of each alternative is determined using Equation (18), and is displayed in Table 11.

$$QU_i = \frac{R_i}{R_0} \quad (18)$$

where,  $i = 1, 2, \dots, m$ . ' $R_0$ ' is the relative significance of the ideal robot alternative (Robot 0) indicated in Table 11.

**Table 11.** Quantitative utility degree of the robot alternatives.

Alternatives	C	R	HC	LC	V	$R_i$	$QU_i$	%
<b>Robot 0</b>	0.00732	0.00577	0.01591	0.03404	0.02125	$0.13688 = R_0$	-	-
<b>Robot 1</b>	0.02603	0.02714	0.01591	0.02894	0.01771	0.07872	0.57509	57.509
<b>Robot 2</b>	0.01952	0.01845	0.01491	0.01532	0.02125	0.07412	0.54150	54.150
<b>Robot 3</b>	0.01464	0.00923	0.01399	0.00613	0.01299	0.06912	0.50494	50.494
<b>Robot 4</b>	0.00732	0.02714	0.00654	0.00545	0.00886	0.04579	0.33450	33.450
<b>Robot 5</b>	0.01220	0.00923	0.01308	0.00681	0.00649	0.06650	0.48578	48.578
<b>Robot 6</b>	0.02034	0.01845	0.01061	0.02043	0.00797	0.06117	0.44688	44.688
<b>Robot 7</b>	0.02278	0.02307	0.01407	0.03064	0.00827	0.07172	0.52396	52.396
<b>Robot 8</b>	0.01464	0.00577	0.01012	0.00340	0.01476	0.07040	0.51433	51.433
<b>Robot 9</b>	0.01464	0.01153	0.01044	0.00851	0.01476	0.06655	0.48618	48.618
<b>Robot 10</b>	0.02278	0.02307	0.01194	0.03404	0.01476	0.07949	0.58074	58.074
<b>Robot 11</b>	0.01790	0.01153	0.01407	0.03404	0.00886	0.08617	0.62955	62.955
<b>Robot 12</b>	0.01139	0.00923	0.01012	0.02383	0.01771	0.09336	0.68203	68.203

(Source: authors' own composition).

#### 4. Results and Validation

The closeness coefficient distances ( $CCD_i$ ) and the quantitative utility ( $QU_i$ ) degree of the alternatives are determined in Tables 9 and 11, respectively. The alternative rankings are proposed based on the values shown in Table 12. The alternative with the lowest  $CCD_i$  and highest  $QU_i$  values is termed as the best robot choice, while the alternative with the highest  $CCD_i$  and lowest  $QU_i$  is termed as the worst one. Table 12 shows the alternative rankings by these two hybrid systems.

**Table 12.** Ranking of robots by TOPSIS-ARAS and COPRAS-ARAS hybrid models.

TOPSIS-ARAS Hybrid Model				COPRAS-ARAS Hybrid Model			
Alternatives	$CCD_i$	%	Rank	Alternatives	$QU_i$	%	Rank
<b>Robot 1</b>	0.50707	50.707	5	<b>Robot 1</b>	0.57509	57.509	4
<b>Robot 2</b>	0.51463	51.463	6	<b>Robot 2</b>	0.54150	54.150	5
<b>Robot 3</b>	0.54794	54.794	8	<b>Robot 3</b>	0.50494	50.494	8
<b>Robot 4</b>	0.65795	65.795	12	<b>Robot 4</b>	0.33450	33.450	12
<b>Robot 5</b>	0.55967	55.967	10	<b>Robot 5</b>	0.48578	48.578	10
<b>Robot 6</b>	0.57810	57.810	11	<b>Robot 6</b>	0.44688	44.688	11
<b>Robot 7</b>	0.49873	49.873	4	<b>Robot 7</b>	0.52396	52.396	6
<b>Robot 8</b>	0.54569	54.569	7	<b>Robot 8</b>	0.51433	51.433	7
<b>Robot 9</b>	0.55207	55.207	9	<b>Robot 9</b>	0.48618	48.618	9
<b>Robot 10</b>	0.44365	44.365	3	<b>Robot 10</b>	0.58074	58.074	3
<b>Robot 11</b>	0.34017	34.017	2	<b>Robot 11</b>	0.62955	62.955	2
<b>Robot 12</b>	0.28805	28.805	1	<b>Robot 12</b>	0.68203	68.203	1

(Source: authors' own composition).

These proposed rankings are now validated using the same CRITIC generated objective criteria weights by using eight other solo MCDM tools, namely, TOPSIS, COPRAS, ARAS, WSM, WPM, WASPAS, MOORA, and MULTIMOORA, which are listed in the following sub-sections.

#### 4.1. Validation Using TOPSIS Method

The same robot selection MCDM problem is validated by the TOPSIS method using the same criterion weights. The steps of the TOPSIS method are nearly identical to the TOPSIS-ARAS hybrid model, with two exceptions. The traditional TOPSIS method does not require the ideal alternative (Robot 0) and the computation of closeness coefficient distances ( $CCD_i$ ). In this case, an alternative ranking is proposed based on the relative closeness coefficient ( $RCC_i^{(topsis)}$ ) values shown in Table 13. The preference ranking order of the robot alternatives are made according to the decreasing closeness coefficient values shown in Table 13. Table 13 shows the calculated PIS, NIS, coefficient values, and the ranking of the alternatives by the TOPSIS method.

**Table 13.** Ranking of robots by TOPSIS method.

Alternatives	PIS	NIS	$RCC_i^{(topsis)}$	Rank
Robot 1	0.09701	0.10230	0.51327	5
Robot 2	0.08654	0.08323	0.49024	6
Robot 3	0.10345	0.07978	0.43541	8
Robot 4	0.13258	0.06511	0.32937	12
Robot 5	0.10976	0.07983	0.42107	11
Robot 6	0.09303	0.06906	0.42607	10
Robot 7	0.09209	0.09829	0.51629	4
Robot 8	0.11165	0.08644	0.43638	7
Robot 9	0.09733	0.07453	0.43367	9
Robot 10	0.08230	0.11152	0.57537	3
Robot 11	0.06195	0.12250	0.66415	2
Robot 12	0.04653	0.11233	0.70709	1

(Source: authors' own composition).

#### 4.2. Validation Using COPRAS Method

The steps of the COPRAS method are similar to those of the COPRAS-ARAS hybrid model. Begin with the Table 1 decision matrix, in this method, the ideal alternative (Robot 0) is not required. Alternative ranking is proposed based on the quantitative utility ( $U_i^{(copras)}$ ) values evaluated using Equation (19) and shown in Table 14.

$$U_i^{(copras)} = \left[ \frac{R_i}{R_{\max}} \right] \times 100\% \quad (19)$$

where,  $i = 1, 2 \dots, m$

' $R_{\max}$ ' is the maximum relative significance value of the alternatives. Relative significances and the quantitative utility values of the alternatives are determined and shown in Table 14 along with the alternative ranking.

**Table 14.** Ranking of robots by COPRAS and ARAS method.

COPRAS					ARAS			
Alternatives	$R_i^{copras}$	$U_i^{copras}$	%	Rank	Alternatives	$V_i$	$U_i^{aras}$	Rank
Robot 1	0.09050	0.83369	83.369	4	Robot 0	0.13332 = $V_0$	-	-
Robot 2	0.08538	0.78652	78.652	5	Robot 1	0.07789	0.58421	4
Robot 3	0.08022	0.73899	73.899	8	Robot 2	0.07284	0.54635	6
Robot 4	0.05338	0.49167	49.167	12	Robot 3	0.06805	0.51039	8
Robot 5	0.07750	0.71394	71.394	9	Robot 4	0.05849	0.43876	12
Robot 6	0.07084	0.65256	65.256	11	Robot 5	0.06443	0.48325	10
Robot 7	0.08276	0.76237	76.237	6	Robot 6	0.05990	0.44927	11
Robot 8	0.08203	0.75564	75.564	7	Robot 7	0.07072	0.53044	7
Robot 9	0.07729	0.71201	71.201	10	Robot 8	0.07487	0.56162	5
Robot 10	0.09173	0.84497	84.497	3	Robot 9	0.06477	0.48581	9
Robot 11	0.09980	0.91931	91.931	2	Robot 10	0.07849	0.58873	3
Robot 12	0.10856	1	100	1	Robot 11	0.08520	0.63907	2
$R_{\max}$	0.10856				Robot 12	0.09365	0.68260	1

(Source: authors' own composition).

#### 4.3. Validation Using ARAS Method

Since the ARAS method is based on the principle of measuring the degree of utility from the ideal alternative, an ideal alternative (Robot 0) must be considered here, and the conversion into beneficial criteria, by taking the reciprocal values of the non-beneficial criteria, is also required before normalization, because the ARAS method cannot handle maximizing and minimizing criteria separately. As a result, starting with Table 6, a customized decision matrix is followed by linear normalization using Equation (13). In this case, optimality values ( $V_i$ ) and the degree of utility ( $U_i^{(aras)}$ ) of each alternative are calculated using Equations (20) and (21), respectively. Table 14 shows the alternative ranking based on the decreasing degree of utility values.

$$V_i = \sum_{j=1}^n D_{ij}^a \quad (20)$$

$$U_i^{aras} = \frac{V_i}{V_0} \quad (21)$$

where,  $i = 1, 2 \dots, m$ ;  $j = 1, 2 \dots, n$ . ' $V_0$ ' is the optimality value of the ideal alternative (Robot 0).

#### 4.4. Validation Using MOORA and MULTIMOORA Method

Brauers and Zavadskas [79] introduced MOORA in 2006, which measures the net weighted performance ( $y_i$ ) of each alternative. Later, Brauers and Zavadskas [80,81] extended the MOORA method, with a full multiplicative form, developing a new model called MULTIMOORA. The initial steps of MOORA and MULTIMOORA are identical to the TOPSIS method (until the normalization process). Following normalization, the net weighted performance ( $y_i$ ) for MOORA and the utility values ( $U_i^{multimoora}$ ) for MULTIMOORA of each alternative are calculated using Equations (22) and (23), and are shown in Table 15. The ranking of robots by MOORA and MULTIMOORA are provided in Table 15.

$$y_i = \sum_{j=1}^g w_j N_{ij} - \sum_{j=g+1}^n w_j N_{ij} \quad (22)$$

$$U_i^{multimoora} = \frac{\prod_{j=1}^g N_{ij}^{w_j}}{\prod_{j=g+1}^n N_{ij}^{w_j}} \quad (23)$$

where,  $i = 1, 2 \dots, m$ ;  $j = 1, 2 \dots, n$ . ' $g$ ' and ' $(n-g)$ ' are the number of beneficial and non-beneficial criteria. The subtraction (second portion) and the denominator part of Equations (22) and (23) represent the non-beneficial criteria, whereas, the first portion and the numerator part of Equations (22) and (23) represent the beneficial criteria.

**Table 15.** Ranking of robots by MOORA and MULTIMOORA method.

MOORA			MULTIMOORA		
Alternatives	$y_i$	Rank	Alternatives	$U_i^{multimoora}$	Rank
Robot 1	0.04626	5	Robot 1	0.79880	4
Robot 2	0.06009	4	Robot 2	0.79836	5
Robot 3	0.04145	6	Robot 3	0.70231	8
Robot 4	−0.03733	12	Robot 4	0.52626	12
Robot 5	0.02456	10	Robot 5	0.65643	10
Robot 6	0.00906	11	Robot 6	0.67793	9
Robot 7	0.03439	9	Robot 7	0.73838	6
Robot 8	0.03551	7	Robot 8	0.64576	11
Robot 9	0.03527	8	Robot 9	0.71167	7
Robot 10	0.06207	3	Robot 10	0.81755	3
Robot 11	0.10233	2	Robot 11	0.92745	2
Robot 12	0.11561	1	Robot 12	1.04453	1

(Source: authors' own composition).

#### 4.5. Validation Using WSM, WPM, and WASPAS Method

WSM is the most basic and widely-used MCDM method. WSM uses Equation (26) to calculate the weighted sum ( $WS_i$ ) of the alternatives, as shown in Table 16. In this method, the decision matrix shown in Table 1 is normalized using Equations (24) and (25), depending on the nature of the criteria.

$$\text{For beneficial criteria, } N_{ij}^{(w)} = \frac{e_{ij}}{e_j^{\max}} \quad (24)$$

$$\text{For non – beneficial criteria, } N_{ij}^{(w)} = \frac{e_j^{\min}}{e_{ij}} \quad (25)$$

$$WS_i = \sum_{j=1}^n (N_{ij}^{(w)} \times w_j) \quad (26)$$

where,  $i = 1, 2 \dots, m$ ;  $j = 1, 2 \dots, n$ . ' $e_j^{\max}$ ' and ' $e_j^{\min}$ ' are the maximum and minimum values of the  $j$ th criteria. ' $w_j$ ' are the criteria weightages.

In the WPM method, the weighted product ( $WP_i$ ) of the alternatives are determined using Equation (27) and presented in Table 16.

$$WP_i = \prod_{j=1}^n (N_{ij}^{(w)})^{w_j} \quad (27)$$

where,  $i = 1, 2 \dots, m$ ;  $j = 1, 2 \dots, n$

WASPAS is a combination of WSM and WPM. In this method, the weighted sum and weighted product values are combined using Equation (28) to determine a joint generalized criterion ( $J_i$ ) of the alternatives, as shown in Table 16.

$$J_i = \lambda WS_i + (1 - \lambda) WP_i \quad (28)$$

where,  $i = 1, 2 \dots, m$ ;  $j = 1, 2 \dots, n$ . The value of ' $\lambda$ ' ranges from  $0 \leq \lambda \leq 1$ . When  $\lambda = 0$ , the first part of Equation (28) was eliminated and took the form of WPM, and when  $\lambda = 1$ , it took the form of WSM, as the second part of Equation (28) was eliminated. In this present analysis,  $\lambda = 0.5$  is used to give equal importance to both WSM and WPM. The ranking of robots by these three methods are proposed in Table 16.

**Table 16.** Ranking of robots by WSM, WPM, and WASPAS method.

WSM			WPM			WASPAS		
Alternatives	$WS_i$	Rank	Alternatives	$WP_i$	Rank	Alternatives	$J_i$	Rank
Robot 1	0.62379	3	Robot 1	0.52187	4	Robot 1	0.57283	4
Robot 2	0.58215	5	Robot 2	0.52158	5	Robot 2	0.55186	5
Robot 3	0.52531	8	Robot 3	0.45883	8	Robot 3	0.49207	7
Robot 4	0.43382	12	Robot 4	0.34381	12	Robot 4	0.38881	12
Robot 5	0.48856	10	Robot 5	0.42885	10	Robot 5	0.45871	10
Robot 6	0.46322	11	Robot 6	0.44290	9	Robot 6	0.45306	11
Robot 7	0.55560	6	Robot 7	0.48239	6	Robot 7	0.51900	6
Robot 8	0.55534	7	Robot 8	0.42188	11	Robot 8	0.48861	8
Robot 9	0.49653	9	Robot 9	0.46494	7	Robot 9	0.48073	9
Robot 10	0.61281	4	Robot 10	0.53411	3	Robot 10	0.57346	3
Robot 11	0.65408	2	Robot 11	0.60591	2	Robot 11	0.63000	2
Robot 12	0.68604	1	Robot 12	0.68240	1	Robot 12	0.68422	1

(Source: authors' own composition).

From the rankings obtained from different applied MCDM methods presented in Tables 12–16, it can be observed that all of the techniques suggest robot 12 and robot 4 as the best and worst choices, respectively. As can be observed from Table 17, even the first three positions are same for all applied techniques, except WSM. Although there



are some ranking variations in the middle-order alternatives, but the outcomes from this analysis are sufficiently consistent enough to provide the exact same best and worst results in all cases. Table 18 also shows that the Spearman rank correlation coefficient (SCC) is greater than 0.8 in all cases, implying that the current proposed rankings have a strong rank correlation with each other. Furthermore, all of the applied MCDM approaches have SCC greater than 0.9, with the final ranking demonstrating their effectiveness in this ongoing decision-making investigation. Table 17 compares the current rankings to the previous researcher results, and the final ranking of robots is also proposed in Table 17 using the Copeland method.

**Table 17.** Ranking comparisons among different MCDM methods.

Presents Rankings											
Alternatives	TOPSIS-ARAS	COPRAS-ARAS	TOPSISCOPRAS		ARAS	MOORA (Ratio System)	MULTI MOORA	WSM	WPM	WASPAS	Final Ranking by Copeland Method
Robot 1	5	4	5	4	4	5	4	3	4	4	4
Robot 2	6	5	6	5	6	4	5	5	5	5	5
Robot 3	8	8	8	8	8	6	8	8	8	7	8
Robot 4	12	12	12	12	12	12	12	12	12	12	12
Robot 5	10	10	11	9	10	10	10	10	10	10	10
Robot 6	11	11	10	11	11	11	9	11	9	11	11
Robot 7	4	6	4	6	7	9	6	6	6	6	6
Robot 8	7	7	7	7	5	7	11	7	11	8	7
Robot 9	9	9	9	10	9	8	7	9	7	9	9
Robot 10	3	3	3	3	3	3	3	4	3	3	3
Robot 11	2	2	2	2	2	2	2	2	2	2	2
Robot 12	1	1	1	1	1	1	1	1	1	1	1
Previous proposed rankings											
References	Alternatives	WSM	WPM	WASPAS	MOORA		Reference point	MULTIMOORA			
					Ratio system						
Karande et al. (2016) [1]	Robot 1	6	9	7	9		11	4			
	Robot 2	4	5	5	5		7	3			
	Robot 3	5	4	4	4		2	6			
	Robot 4	12	12	12	12		11	12			
	Robot 5	9	8	9	7		2	10			
	Robot 6	11	11	11	11		7	11			
	Robot 7	10	10	10	10		9	8			
	Robot 8	1	2	2	1		1	9			
	Robot 9	8	6	6	6		5	7			
	Robot 10	7	7	8	8		9	5			
	Robot 11	3	3	3	3		5	2			
	Robot 12	2	1	1	2		2	1			

(Source: Karande et al., 2016; Authors' own composition).

**Table 18.** Spearman rank correlation coefficient among the present proposed rankings.

	COPRAS-ARAS	TOPSIS-ARAS	COPRAS	ARAS	TOPSIS	MOORA	MULTI MOORA	WSM	WPM	WASPAS	Final Rank
COPRAS-ARAS	-	0.97902	0.99301	0.97902	0.97203	0.94406	0.91608	0.99301	0.91608	0.99301	1
TOPSIS-ARAS		-	0.97203	0.95105	0.99301	0.88112	0.89510	0.96503	0.89510	0.97203	0.97902
COPRAS			-	0.97203	0.95804	0.93007	0.89510	0.98601	0.89510	0.98601	0.99301
ARAS				-	0.94406	0.93706	0.83916	0.97203	0.83916	0.95804	0.97902
TOPSIS					-	0.87413	0.90210	0.95804	0.90210	0.96503	0.97203
MOORA						-	0.87413	0.93007	0.87413	0.95105	0.94406
MULTI MOORA							-	0.90909	1	0.93706	0.91608
WSM								-	0.90909	0.98601	0.99301
WPM									-	0.93706	0.91608
WASPAS										-	0.99301
Final rank											-

(Source: authors' own composition).

From Table 17, it can be observed that the previous rankings proposed by Karande et al. [1] are inconsistent, as the best robot choices are dissimilar for different methods. Karande et al. [1] found robot 12 to be the best alternative by WPM, WASPAS, and MULTIMOORA, while WSM and MOORA suggested that robot 8 is the best choice. Hence, there is still some confusion regarding the best robot alternative between robot 8 and robot 12 from the previous outcomes, and as a result, Karande et al. [1] completely fail to achieve the primary goal of selecting the best robot among the 12 available alternatives. Similarly, using a two-phase combined approach of DEA and a weighted overall efficiency ranking method, Mondal and Chakraborty [4] proposed robot 12 as the best alternative. Although the decision by Mondal and Chakraborty [4] is accurate and matches with the present analysis outcomes, they failed to suggest the worst robot alternative. Mondal and Chakraborty [4] proposed a partial ranking order of the robot alternatives for the first three positions only, i.e., first, second, and third. In any decision-making analysis, suggesting the worst option is just as equally important as proposing the best one. Therefore, the analysis carried out by Mondal and Chakraborty [4] is incomplete and inadequate. On the other hand, the current study proposes a complete preference ranking order of the alternatives. The current rankings demonstrate its stability and consistency, as all of the applied methods suggest that robot 12 is the best choice followed by robot 11, and robot 4 is the worst among the 12 alternatives. As a result, there is no doubt and confusion about which robots are the best and worst choices, like in the previous two cases. Even the rankings from the two new hybrid models show very good/strong rank correlation with the other MCDM methods, as revealed in Table 18, demonstrating their good decision-making abilities and consistency in comparison to other techniques. The final ranking of the robots, according to the mode of preference using the Copeland rule can be proposed as follows.

Robot 12 > robot 11 > robot 10 > robot 1 > robot 2 > robot 7 > robot 8 > robot 3 > robot 9 > robot 5 > robot 6 > robot 4.

## 5. Sensitivity Analysis

Sensitivity analysis is a study that demonstrates the effects of variations in input data produced by the MCDM models, and determines the intensity of the model [1]. According to Ustinovichius and Simanaviciene [82], sensitivity analysis was described as “a study of how uncertainty in the model output can be allocated on the model input to various sources of uncertainty”. It is therefore an effective tool to assess the robustness of the results achieved from an MCDM model in the presence of vagueness and uncertainty [1]. The sensitivity analysis thus allows (a) to verify the robustness of the decision-making model results; (b) to recognize the most unpredictable input parameters that trigger major performance variances on the output; and (c) to figure out the range of input parameter values for which the model displays a stable output [1,83]. Zavadskas et al. [84] stated that the outputs generated in an MCDM method are influenced by two input parameters, i.e., criteria weights and performance data. As a consequence, sensitivity analysis is carried out to study the impact of variations in criteria weights on the final alternative rankings [1]. It allows decision makers to analyze the potential of MCDM techniques in ostensible performance trading, fix ambiguity in selection issues, and identify the least sensitive solution [1]. Single dimension weight sensitivity analysis is therefore conducted in this paper to examine the impact of differing criteria weights on the final rankings of the alternatives as obtained using the applied MCDM models [1].

In this method, weight is varied within a feasible range for the most relevant criterion, and the rest of the parameter weights are modified equally to maintain the additive weight restriction,  $\sum_{j=1}^n w_j = 1$  [1]. Since the difference in weight for the most relevant criterion is evenly distributed among the remaining criteria, it is often called non-proportional sensitivity analysis [1]. Typically, a criterion with the highest weight means that it has the greatest effect on the alternatives rating, so it can be regarded as the most relevant criterion [1]. Since this approach is based on the principle of additivity of weights, and

since the weights of the criteria cannot be negative, the maximum possible weight of the chosen criterion is thus restricted [1]. Therefore, the potential range within which the weight of the chosen criterion can be varied needs to be established [1]. In this case, it is possible to minimize the weight of the most important criterion to 0 and raise it to  $w_j^*$  [1]. Using Equation (29), the value of  $w_j^*$  can be obtained as follows [1].

$$w_j^* = \left[ w_j^{\max} + (n - 1) \times w_j^{\min} \right] \quad (29)$$

where,  $w_j^{\max}$  (LC = 0.25157) and  $w_j^{\min}$  (HC = 0.16169) are the maximum and minimum criteria weights, respectively. 'n = 5' is the number of criteria. Increasing the weight of the most significant criterion above  $w_j^*$  would make the weight of the lowest criterion negative [1]. The local weight stability interval shows the range of weight in which the ranking of the best alternatives remains unchanged, while the global weight stability interval determines the range of weights within which the overall rank of the alternatives remain unaltered for any particular technique, with respect to the results and rankings obtained using the actual criteria weightages [1].

The most important criterion for carrying out single dimensional weight sensitivity analysis is first defined as LC with the highest priority weight of 0.25157. Its weight now varies within a feasible range of  $0 \geq w_{LC} \geq 0.89834$ , while retaining the restriction of weight additivity [1]. The weight of criterion LC cannot be increased above 0.89834, since the lowest criteria weights, i.e., HC parameter will become negative [1]. Therefore, 20 new sets of criterion weights are created, as shown in Table 19, and this problem is again solved with those new sets of criterion weights to obtain the robot alternative rankings using the adopted methods [1]. The following paper also provides intervals of local and global weight stability for each MCDM process, which are shown in Table 20. Figures 2–11 show the effects on the alternative rankings due to variation in criteria weights by 10 different adopted MCDM tools.

**Table 19.** Twenty new sets of criteria weights.

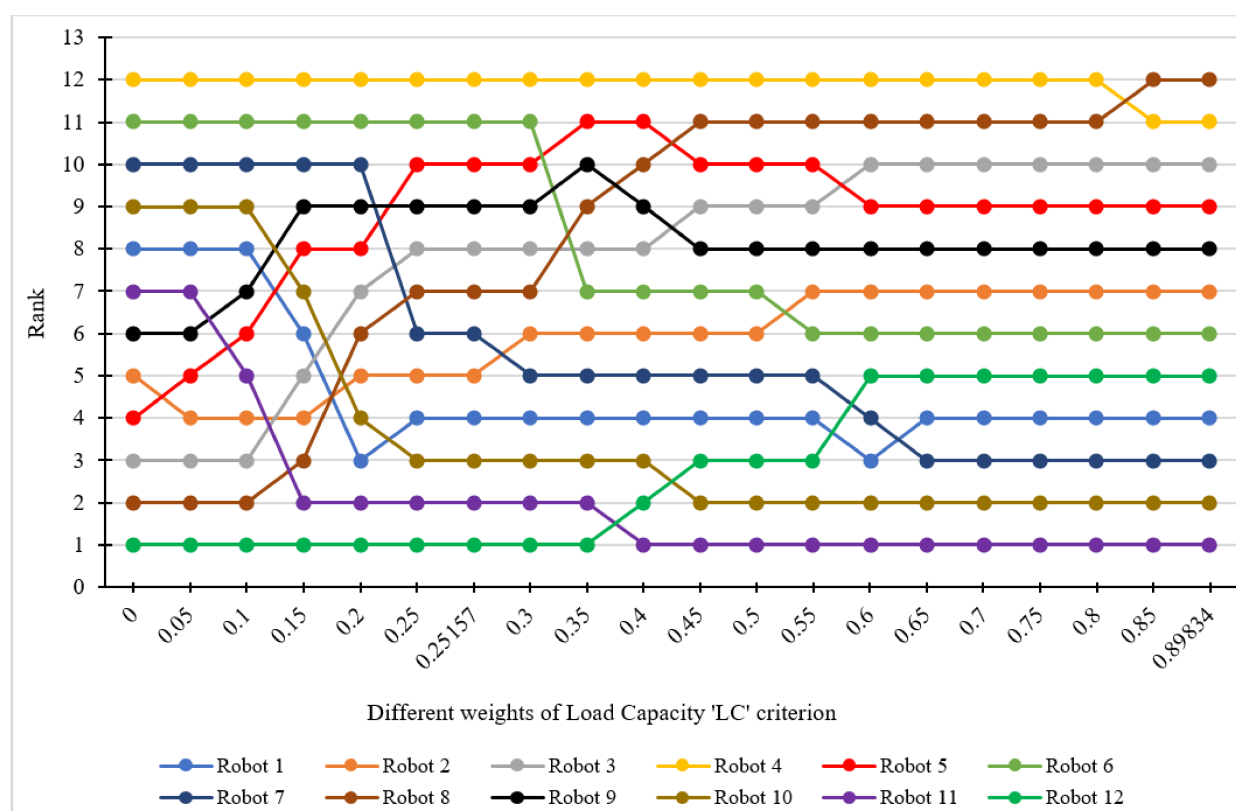
Sets of Criteria Weights	C	R	HC	LC	V
Set 1	0.27440	0.26249	0.22459	0	0.23853
Set 2	0.26190	0.24999	0.21209	0.05	0.22603
Set 3	0.24940	0.23749	0.19959	0.1	0.21353
Set 4	0.23690	0.22499	0.18709	0.15	0.20103
Set 5	0.22440	0.21249	0.17459	0.2	0.18853
Set 6	0.21190	0.19999	0.16209	0.25	0.17603
Set 7 (Actual weights)	0.21150	0.19960	0.16169	0.25157	0.17563
Set 8	0.19940	0.18749	0.14959	0.3	0.16353
Set 9	0.18690	0.17499	0.13709	0.35	0.15103
Set 10	0.17440	0.16249	0.12459	0.4	0.13853
Set 11	0.16190	0.14999	0.11209	0.45	0.12603
Set 12	0.14940	0.13749	0.09959	0.5	0.11353
Set 13	0.13690	0.12499	0.08709	0.55	0.10103
Set 14	0.12440	0.11249	0.07459	0.6	0.08853
Set 15	0.11190	0.09999	0.06209	0.65	0.07603
Set 16	0.09940	0.08749	0.04959	0.7	0.06353
Set 17	0.08690	0.07499	0.03709	0.75	0.05103
Set 18	0.07440	0.06249	0.02459	0.8	0.03853
Set 19	0.06190	0.04999	0.01209	0.85	0.02603
Set 20	0.04981	0.03791	0	0.89834	0.01394

(Source: authors' own composition).

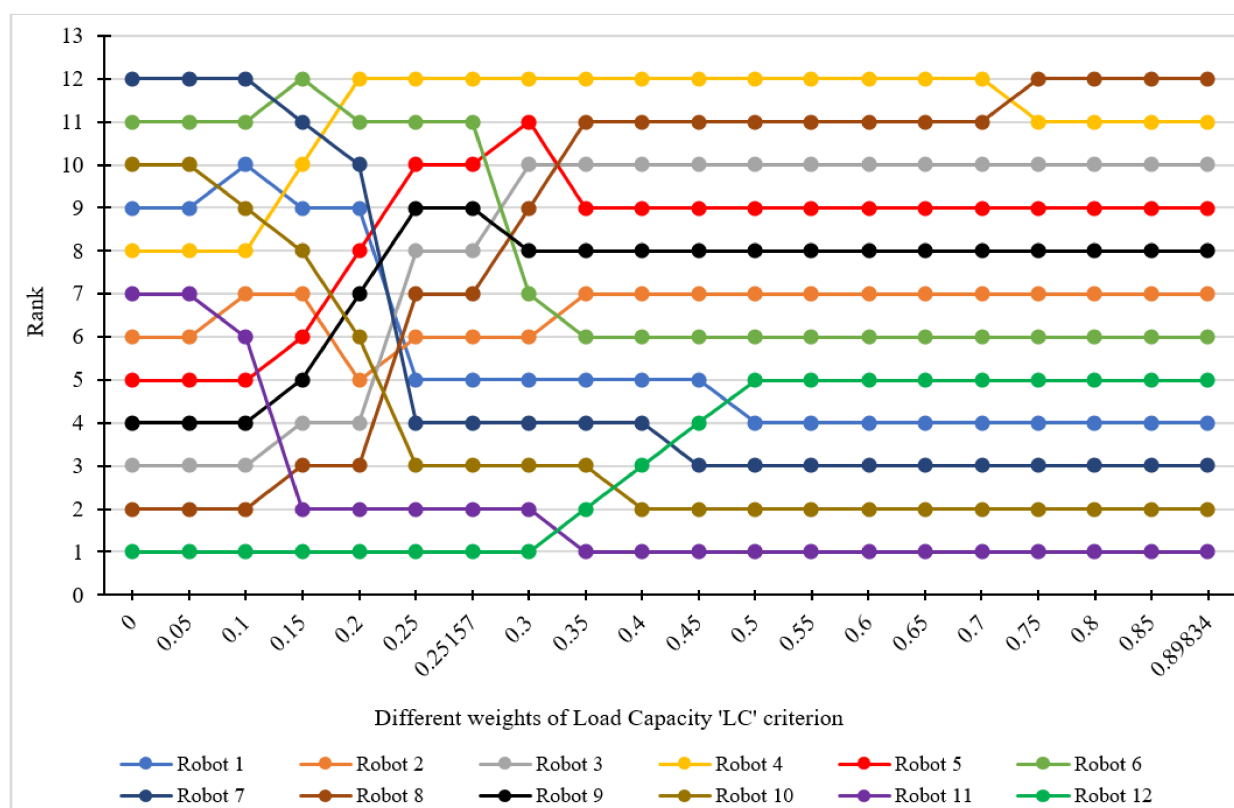
**Table 20.** Local and global weight stability intervals of five MCDM models.

MCDM Methods	Weight Stability Intervals	
	Local	Global
COPRAS-ARAS	$0 \geq w_R \geq 0.35$	$0.25 \geq w_R \geq 0.25157$
TOPSIS-ARAS	$0 \geq w_R \geq 0.3$	$0.25 \geq w_R \geq 0.25157$
TOPSIS	$0 \geq w_R \geq 0.25157$	$0.25 \geq w_R \geq 0.25157$
COPRAS	$0 \geq w_R \geq 0.35$	$0.25 \geq w_R \geq 0.25157$
ARAS	$0.1 \geq w_R \geq 0.3$	$0.25 \geq w_R \geq 0.25157$
MOORA	$0 \geq w_R \geq 0.3$	$0.25 \geq w_R \geq 0.25157$
MULTIMOORA	$0.05 \geq w_R \geq 0.4$	NIL
WSM	$0.05 \geq w_R \geq 0.3$	NIL
WPM	$0.05 \geq w_R \geq 0.4$	NIL
WASPAS	$0.05 \geq w_R \geq 0.35$	$0.25 \geq w_R \geq 0.25157$

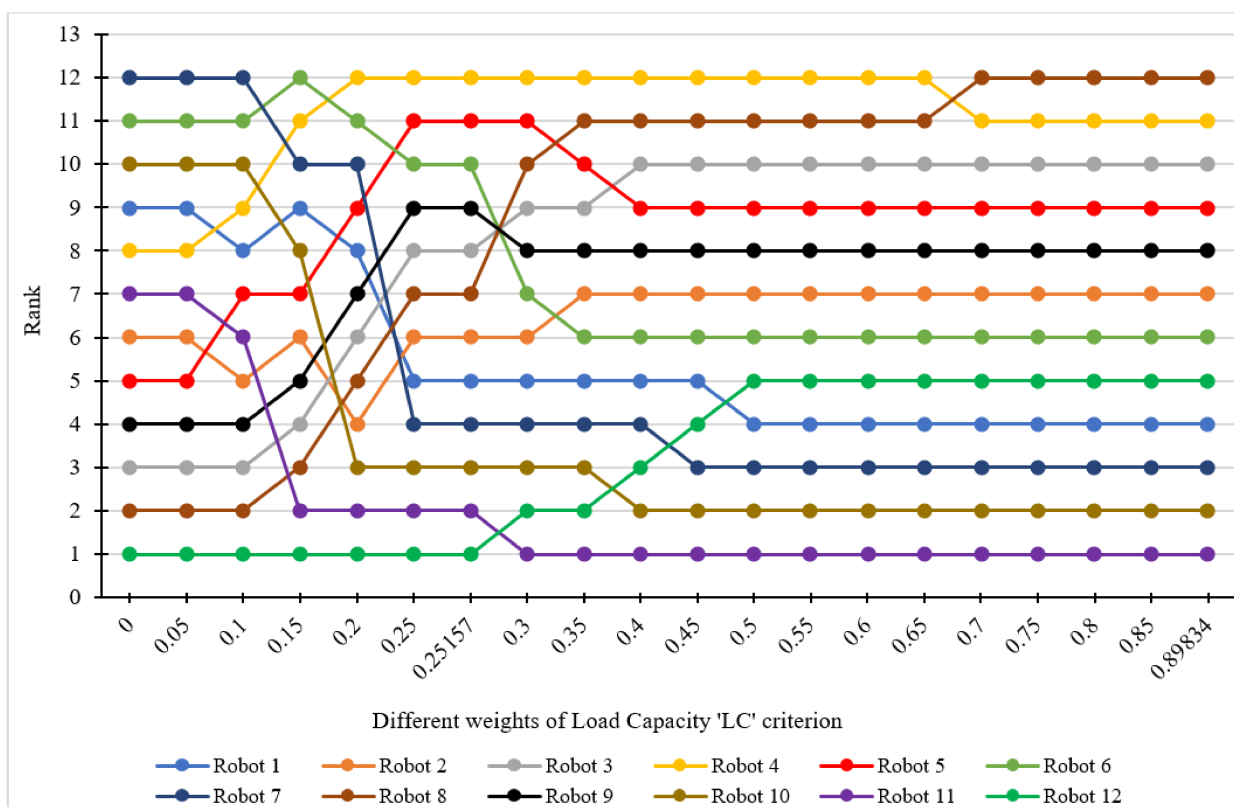
(Source: authors' own composition).

**Figure 2.** Robot ranking variations in the COPRAS-ARAS hybrid model. (Source: authors' own composition. Created using a Microsoft chart).

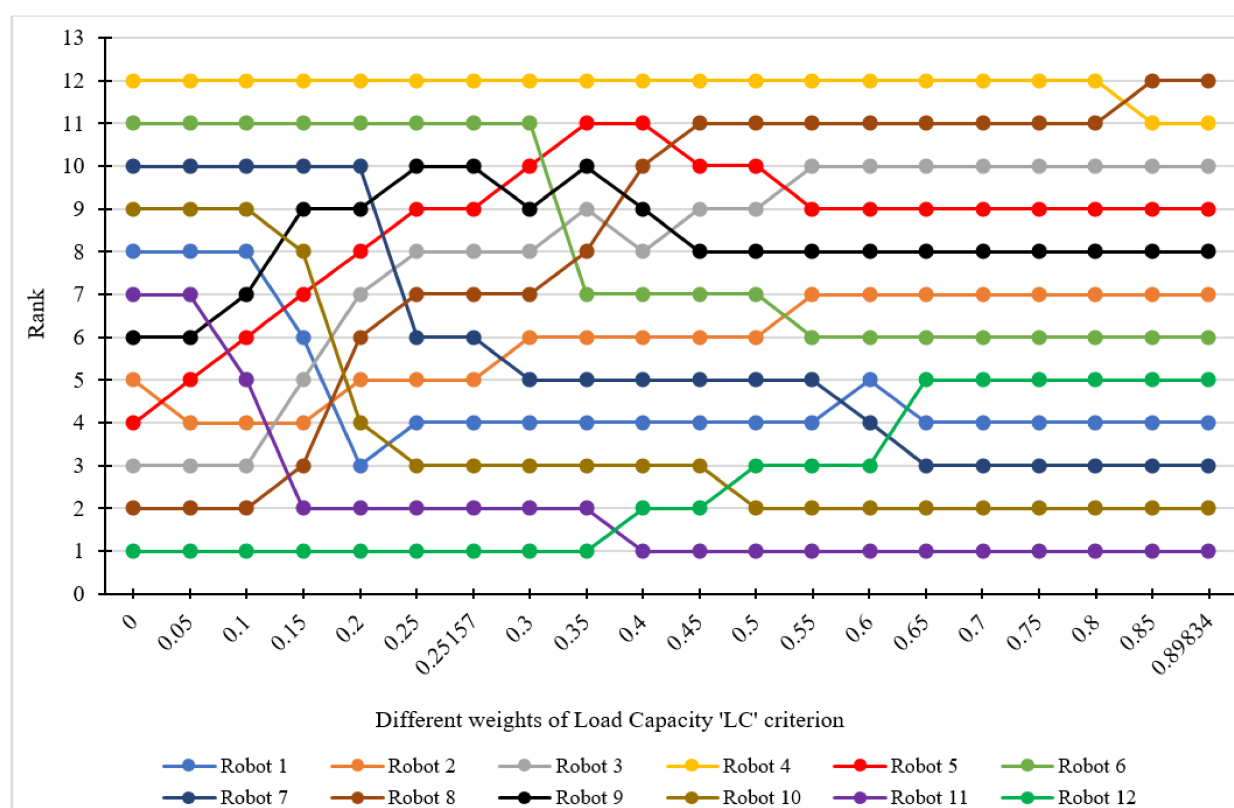




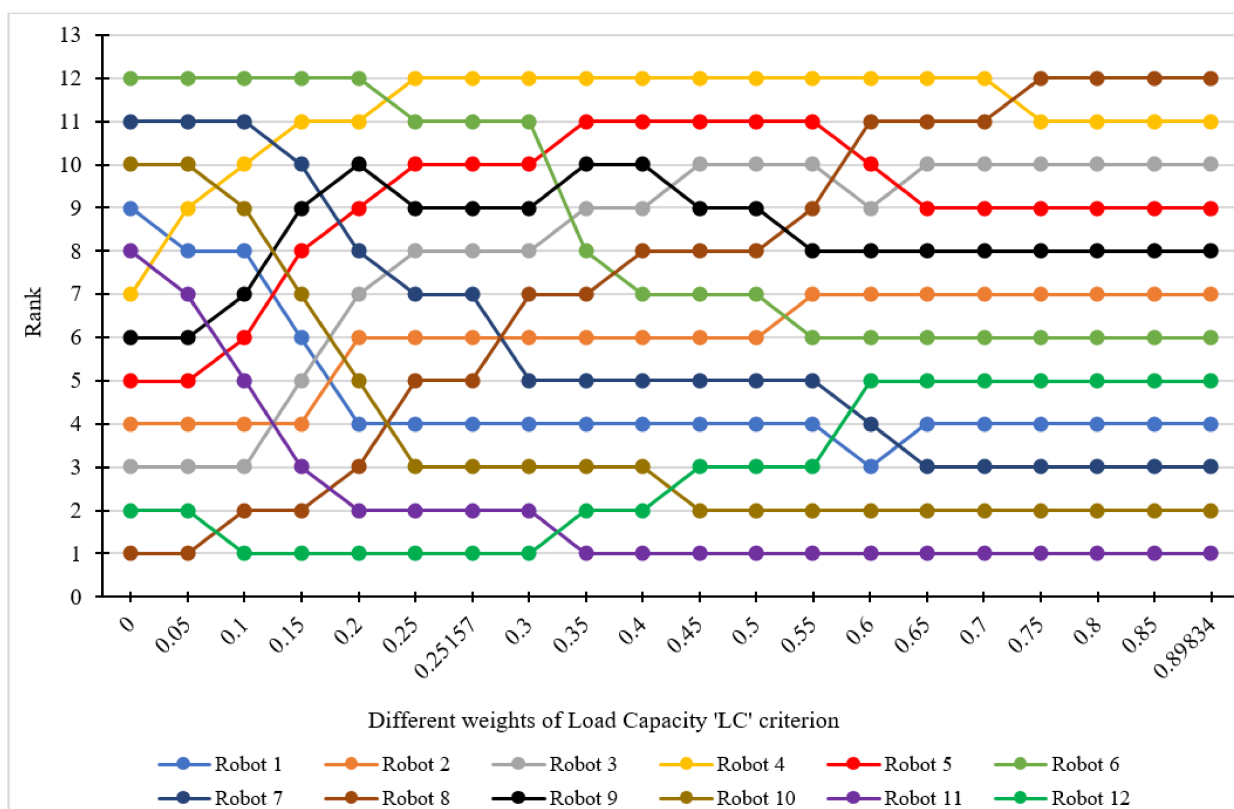
**Figure 3.** Robot ranking variations in the TOPSIS-ARAS hybrid model. (Source: authors' own composition. Created using a Microsoft chart).



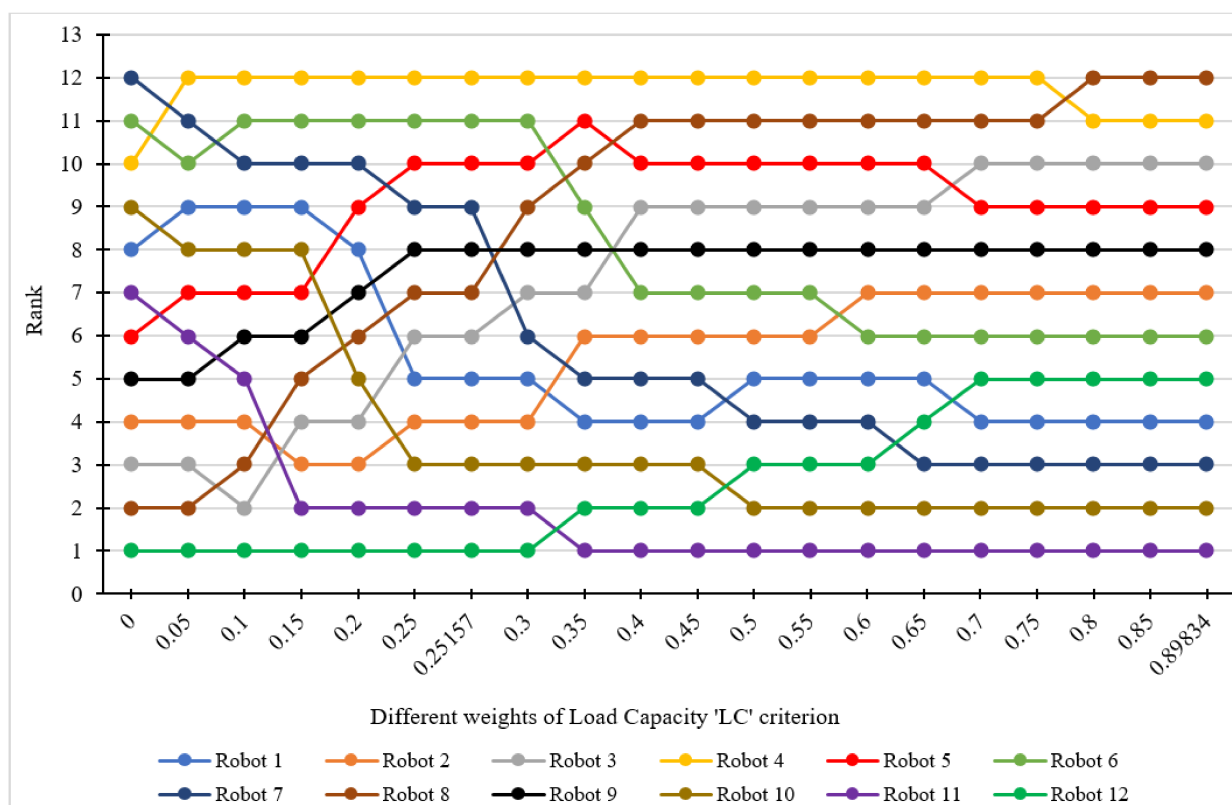
**Figure 4.** Robot ranking variations in the TOPSIS model. (Source: authors' own composition. Created using a Microsoft chart).



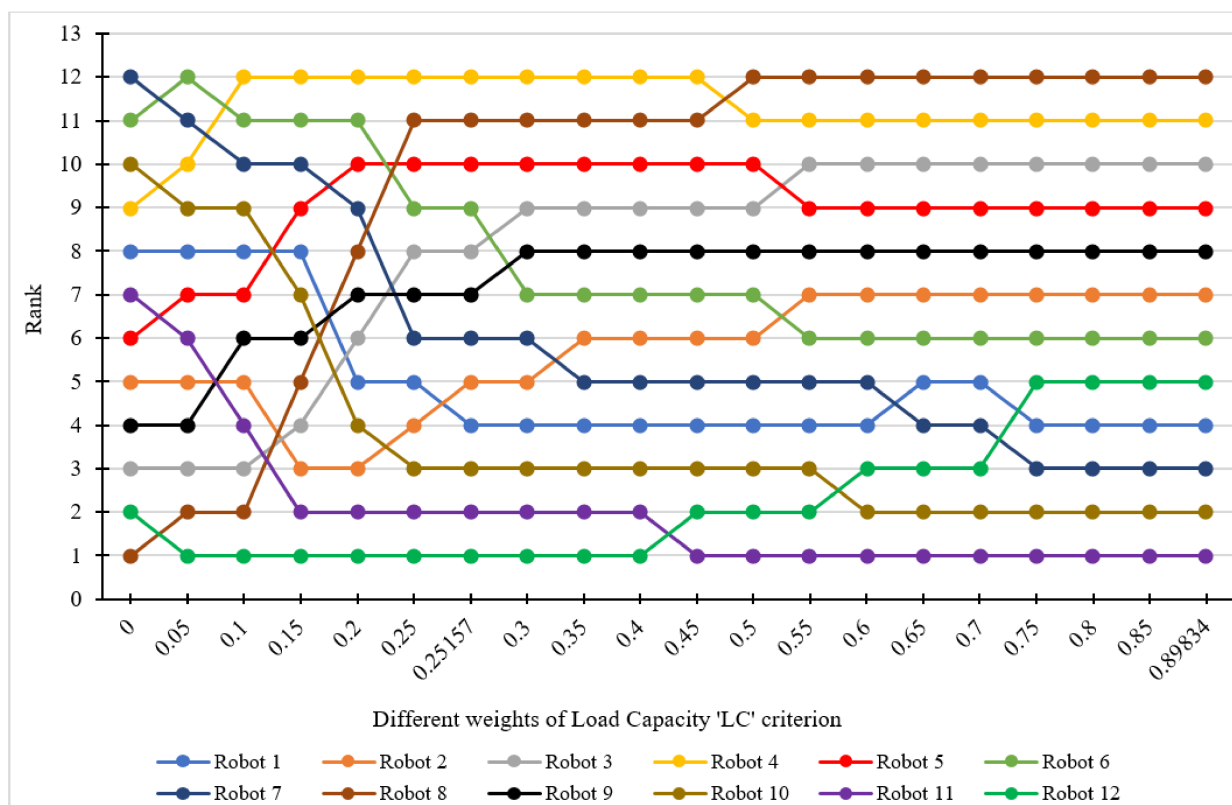
**Figure 5.** Robot ranking variations in the COPRAS model. (Source: authors' own composition. Created using a Microsoft chart).



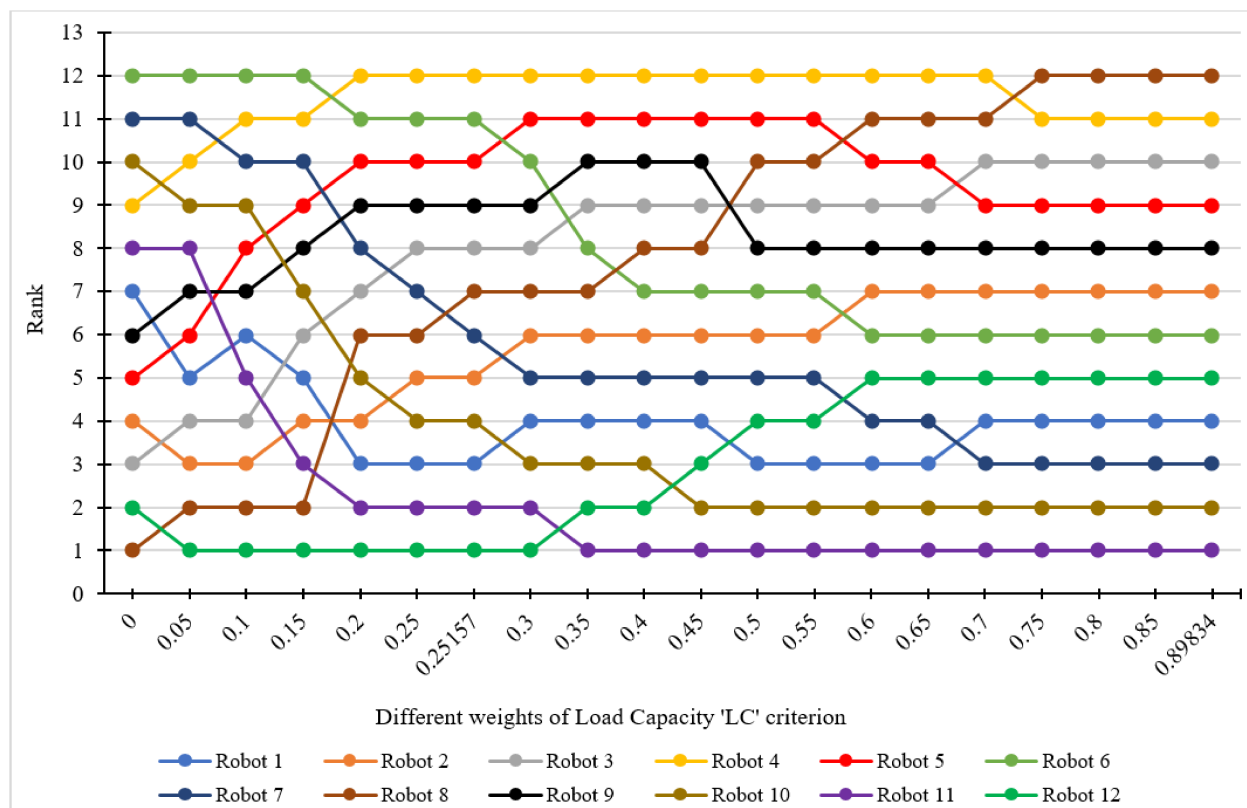
**Figure 6.** Robot ranking variations in the ARAS model. (Source: authors' own composition. Created using a Microsoft chart).



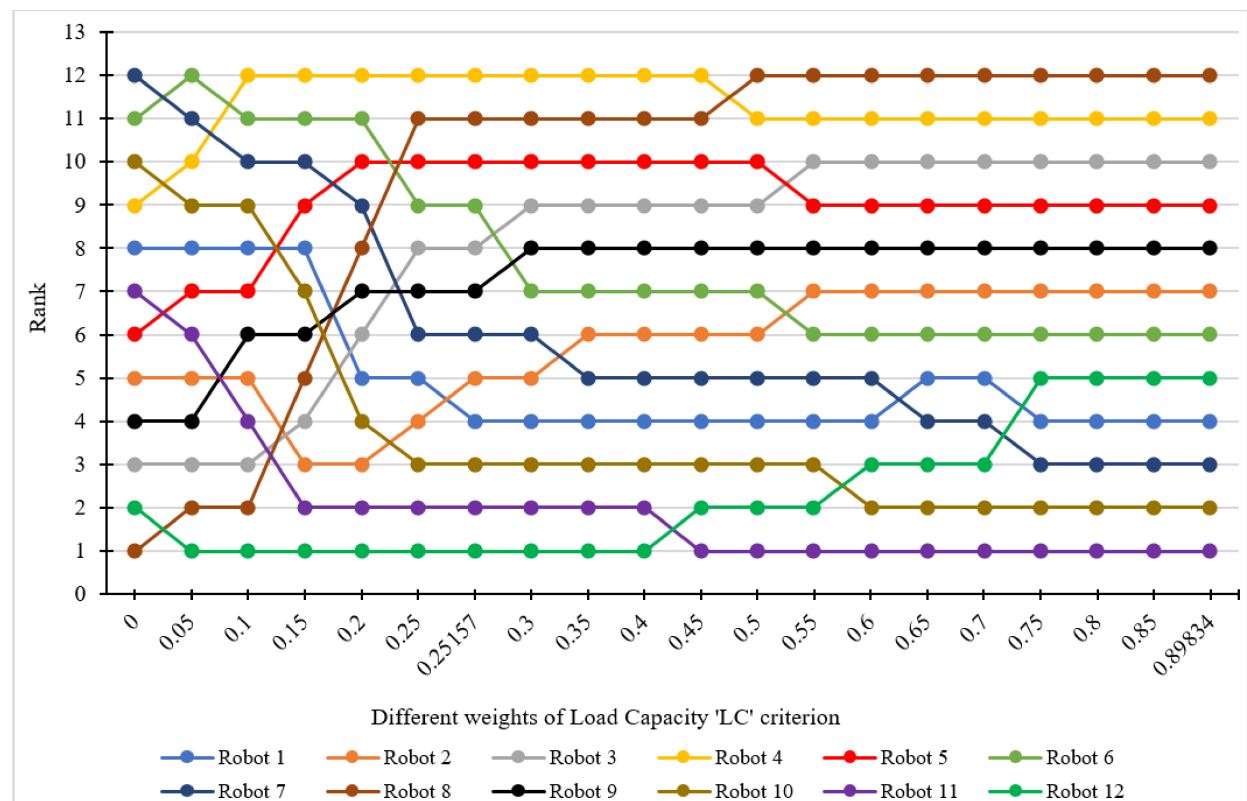
**Figure 7.** Robot ranking variations in the MOORA model. (Source: authors' own composition. Created using a Microsoft chart).



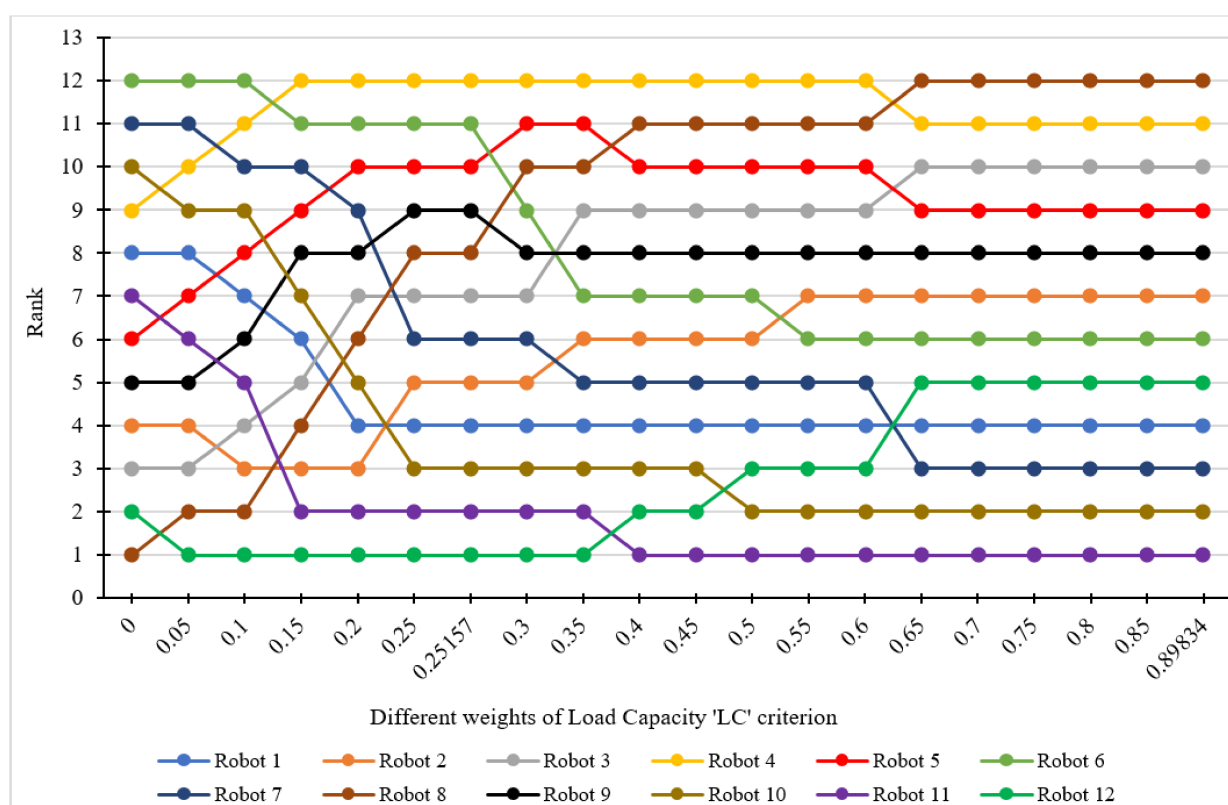
**Figure 8.** Robot ranking variations in the MULTIMOORA model. (Source: authors' own composition. Created using a Microsoft chart).



**Figure 9.** Robot ranking variations in the WSM model. (Source: authors' own composition. Created using a Microsoft chart).



**Figure 10.** Robot ranking variations in the WPM model. (Source: authors' own composition. Created using a Microsoft chart).



**Figure 11.** Robot ranking variations in the WASPAS model. (Source: authors' own composition. Created using a Microsoft chart).

The illustrated graphs depict that all of the alternative rankings by the applied MCDM techniques are affected to some extent by the variation of criteria weights. It is clear from Figures 2–11 that the employed tools gradually gain stability as they move right, to the higher weight region. There are a few more verdicts that can be made from this sensitivity analysis. We will go over some key points one by one. To begin with, the robustness of the implemented MCDM approaches, the local, and global weight stability intervals presented in Table 20, depict that hybrid COPRAS-ARAS, and solo COPRAS MCDM appears to be the most robust and stable method with a maximum local interval (LI) of  $0 \geq w_R \geq 0.35$  and global interval (GI) of  $0.25 \geq w_R \geq 0.25157$ . Although it is difficult to make judgement based on only global weight stability intervals, most of the applied methods have the same GI, except MULTIMOORA, WSM, and WPM, which do not have GI. Despite the fact that MULTIMOORA and WPM have the same LI as COPRAS-ARAS and COPRAS, these two methods lack in dedicated global weight stability intervals, as shown in Table 20, proving their ineffectiveness and inefficient tools for this current analysis. Now, if the sensitivity of any model is taken into account, then ARAS and WSM would be the most appropriate choices. It is also difficult to predict which of these two tools is the most sensitive, because ARAS has the lowest LI followed by WSM and, thus, the most sensitive tool based on the local stability interval, but WSM is more sensitive than ARAS based on the global stability interval, because no GI is found for this approach.

Next, we look at two things: (a) whether the two newly developed hybrid systems, TOPSIS-ARAS and COPRAS-ARAS, were able to fulfil our expectations; (b) whether the hybrid models outperformed the solo techniques. When comparing these two hybrid models to the standalone MCDM tools, TOPSIS, COPRAS, and ARAS, the following decisions can be made. First, as we can see from Table 20, the local stability interval of COPRAS-ARAS is greater than all of the applied tools, particularly ARAS. As a result of integrating COPRAS with ARAS, both the stability and ranking efficiency of the ARAS MCDM is enhanced. As previously being one of the most sensitive tools, the performance

of ARAS improved by incorporating COPRAS, so much so that it later became one of the most robust MCDM systems. Similarly, the TOPSIS-ARAS hybrid model also performs better and has a higher LI than solo TOPSIS and ARAS, making the hybrid model more stable and consistent than the single standalone techniques. Therefore, the overall analysis leads to the conclusion that combining ARAS with TOPSIS and COPRAS improves the efficiency and performance of the individual TOPSIS and ARAS methods to some extent. Furthermore, the consistency, effectiveness, and stability of these two hybrid models are better than the single techniques when used individually.

## 6. Conclusions

This paper examined an industrial robot selection problem using two newly developed CRITIC-embedded TOPSIS-ARAS and COPRAS-ARAS hybrid MCDM systems, and parallelly, significantly boosted and enhanced the previous proposed rankings by removing the complexity, confusion, and vagueness associated with the existing literature. The following two hybrid models were developed with the goal of recommending the best robot for a given industry. The creation of such MCDM models is the primary contribution to the fields of manufacturing and decision theory. At the same time, it contributes toward improving the performance, effectiveness, stability, and efficiency of the solo ARAS and TOPSIS MCDM. From this analysis, it can be concluded that robot 12 is the best choice followed by robot 11 among the 12 alternative robots, and robot 4 should be ignored completely as it is the worst choice by all of the methods. Apart from these, the key concluding remarks and the core contribution to this work can be summarized as follows:

- The two newly developed hybrid MCDM systems provide a very effective and appropriate selection of the best robot alternative for an industry.
- Both of the developed hybrid models prove to be very stable and efficient decision-making tools. COPRAS-ARAS is the one and only tool whose ranking exactly matches with the Copeland-based final proposed ranking and Spearman rank correlation coefficient between the TOPSIS-ARAS hybrid model and the final ranking is as high as 0.97902, indicating its good decision-making potential and ability.
- As discussed under the results and validation section, the previous proposed rankings were clearly unstable. As a result, the current review is more rigorous, strong, and provides a genuine ranking order; thus, it greatly improves the previous literature.
- Both established hybrid MCDM systems are simple, straightforward, systematic, understandable, and rational approaches that can easily fit into any decision-making analysis.
- Several previously mentioned statements are proven during the sensitivity analysis. As a result, the following conclusions can be drawn regarding those specific points.
  - (a) ARAS is a highly sensitive tool, and even minor variations in the input data cause a significant impact on the outcomes.
  - (b) COPRAS outperforms ARAS in terms of efficiency and effectiveness. Moreover, COPRAS is more robust and stable than ARAS in terms of parameter weight variation.
  - (c) In the presence of varying input data, TOPSIS outperforms ARAS in terms of performance stability.
  - (d) Judgement delivered by COPRAS is more efficient and less biased than TOPSIS and WSM-embedded decisions. Moreover, COPRAS has greater consistency than WSM in the presence of data variation.
- Objective weighting estimation methods, such as entropy or CRITIC, are more superior to using subjective weighting methods, such as AHP, BWM, or SWARA. Objective tools are not influenced by the decision makers' views, opinions, knowledge, or experiences; therefore, it can generate more reliable and consistent performance results.
- This study may provide ideas to industries, and address manufacturing concerns, in regard to the installation of automated material handling systems in organizations.



When purchasing new material handling equipment, decision makers can also use these hybrid approaches to select a specific type.

**Limitations:** The following study is entirely based on estimation and mathematical computations. This study does not guarantee that there are no other robots on the market that are better than the proposed one; rather, it suggests that robot 12 is the best option among the 12 alternative robots considered for this analysis. This article only covers one general concept and tries to clear up any confusions that may arise when choosing a suitable robot. Furthermore, MCDM problems are heavily reliant on the parametric weightages, and any variations in the weightage values can affect the performance results. As a result, other weightage estimation tools, such as AHP, SWARA, BWM, entropy, SMART, etc., may produce different criteria weights, which eventually alter the final ranking. If subjective weighting methods, such as AHP, BWM, SWARA, SMART, etc., are involved, it may lead to biased decisions, because subjective tools deal with the relative importance matrix, which is completely dependent on the DM's opinion, views, and judgement; therefore, some inconsistencies and biasedness are associated with the weights produced by the subjective methods. Additionally, the following robot selection problem is performed on a limited number of essential criteria and alternatives; however, there are other alternative robots and parameters that can be considered in addition to these, which can cause the results to deviate [85].

**Future scope:** the following points can be considered in the framework of future studies:

- Other weighting tools, such as Entropy, BWM, SMART, SWARA, etc., can be used to determine the parameter weights, and the differences in alternative rankings can be noted.
- In order to make the selection process more specific and reliable, more parameters and robot alternatives can be considered in addition to these.
- There are numerous MCDM tools available, such as EDAS, CODAS, PROMETHEE, PIV, CoCoSo, and others, which can be used to solve this same robot selection problem, and the results can be compared with these present outcomes.
- Other potential and efficient MCDM tools can be merged to develop new robust hybrid models.
- Lastly, these two newly developed TOPSIS-ARAS and COPRAS-ARAS hybrid MCDM systems can be implemented in a broad variety of areas, such as the banking sector, the health and education sector, the industrial and manufacturing sector, transportation and logistics, etc., in order to expand its applicable areas, and to explore the ability of these novel hybrid models.

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