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Entropy-Based Probabilistic Decision-Making Models for Industrial Robot Selection in Defence Systems

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ABSTRACT

The choice of the right industrial robot is a crucial step in the development of the manufacturing firm because of its impact on the production rate, output, and income-generating capacity of the firm. In the last decades, people have started using tools from Multi-Criteria Decision Making (MCDM) to help them make better decisions. Nevertheless, many questions remain unanswered in the literature regarding the usability of these methods in industrial robot selection. To enhance the ability to evaluate and select industrial robots, this study introduces two new methods of MCDM, which are named Sum Weighted Information (SWI) and Sum Weighted Exponential Information (SWEI). The SWI method is developed from the Weight Information method, and the SWEI method is synthesized by the Exponential Weight Information method. These approaches enhance decision-making accuracy in complex scenarios where criteria weighting is crucial. Results indicate that SWI and SWEI provide robust, interpretable rankings, facilitating well-informed decisions across various domains. The robustness of the proposed method was assessed through a sensitivity analysis and further validated by comparing the ranking outcomes with those obtained using the MOORA MCDM approach. The results demonstrate that the final rankings remain consistent, thereby confirming the stability and reliability of the proposed approach.

Keywords: Multi-criteria decision-making; Arc welding robot; SWI method; SWEI method; Measure of information; Shannon's entropy; Military vehicles

NOMENCLATURE

MCDM	: Multi-criteria decision-making
SWEI	: Sum weighted exponential information
SWI	: Sum weighted information
SAW	: Simple additive weighting
MEW	: Multiplicative exponent weighting
ELECTRE	: ELimination and choice expressing reality
DMIM	: Decision making by information measure
IDM	: Information decision matrix
AHP	: Analytic hierarchy process
TOPSIS	: Technique for order preference by similarity to ideal solution
MOORA	: Multi-objective optimization method by ratio analysis

1. INTRODUCTION

Examining a standard measurement is frequently not sufficient to resolve the complex and disorganized nature of real-world decision-making problems, which would lead to the best outcome. Working in the marketplace necessitates an understanding of the factors that lead to crisis circumstances and insolvency. It is vital to know the parameters that determine the creation and failure of viable alternatives. The analyst uses many criteria techniques to create a single criteria that capture all the essential components of the situation. The decision-maker must balance several competing goals. All fresh ideas and prospective decision variations must be compared using a variety of criteria. A decision-maker evaluates a finite number of options to determine the best and rank them from finest to nastiest, classify them into established homogenous groups, or explain how well each alternative fulfills all the criteria at the same time. There are a variety of approaches for rating a collection of options based on a set of choice criteria. The analyst uses a multi-criteria technique to construct different criteria from various points of view. MCDM is a commonly used decision methodology in scientific knowledge, industry, and government that is founded on the concept of a complex system and can assist in enhancing decision performance and making decision-making clear, more logical, and more effective.

In the actual world, a decision-maker must first comprehend and articulate the circumstances. This step entails determining and assessing stakeholders, various options for possible activities, a huge number of diverse, relevant decision criteria, information kind and superiority, and so on. It appears to be the defining feature of decision-making as a ceremonious methodology. The rules, metrics, and standards that guide decision-making are known as the decision criteria described by Demir, *et al.*[1]. Ye, *et al.*[2] suggested a broad definition of criteria as a tool for comparing options based on a certain

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viewpoint. When developing criteria, the analyst should take into consideration that all participants in the decision-making process must agree on the evaluations that will be drawn from the method. Criteria are metrics, norms, and standards that influence decision-making, as well as a model of preferences between the parts of a collection of actual or fake acts (quite accurate but generally contradictory). Discrete MCDM challenges, which involve choosing between multiple investment projects, people rating difficulties, and financial categorization problems, and are decision-support-focused, are typical types of MCDM problems.

1.1 Motivation for the Study

To explicitly state the increasing role of industrial robots in defense operations and the need for robust decision-making tools to evaluate robot alternatives under multiple conflicting criteria and uncertainty. The introduction highlights the gap in current literature, where many models overlook probabilistic or information-theoretic perspectives in such high-stakes, high-precision environments.

1.2 Practical and Methodological Aims

This subsection now outlines both the practical goal-supporting defense organizations in selecting suitable industrial robots—and the methodological aim—developing and applying entropy-based probabilistic MCDM models (SWI and SWEI) that integrate uncertainty through information theory principles.

1.3 Contributions of the Study

The main contributions in the study are:

- Proposing and applying two entropy-based probabilistic decision models (SWI and SWEI)
- Demonstrating their effectiveness in ranking industrial robot alternatives for defense systems
- Comparing results with the MOORA MCDM to evaluate the robustness of the proposed method
- Offering a probabilistic framework that reduces dependence on subjective inputs.

The structure of the study consists of six sections. Section 2 contains the literature review. The methodology of the study and the approaches of the new SWI and SWEI methods are presented in Section 3. The application of the proposed study is provided in Section 4. The discussion and applicability of the innovative SWI and SWEI methods are demonstrated in Section 5. Finally, the conclusion and limitations of the study are given in Section 6, where the results are summarized.

2. LITERATURE REVIEW

Many even complex questions have been explored in partnership with experts from other fields of research (e.g., mathematics), as Kaplinski[3]. Techniques and planning approaches, as well as decision-making processes, evolve with time Peldschus[4]; Zavadskas, *et al.*[5]; Jakimavicius and Burinskiene[6]; Ozkan, Baris, and Bulkan[7]; Ecer[8]; Biswas, *et al.*[9]; Wei[10]; Tao[11], *et al.*; Stevic, *et al.*[12]; Kannan, *et al.*[13]; Brunelli and Rezaei[14].

MacCrimmon was the first to understand the need to associate MCDM approaches, the importance of selected difficulties, and the proposed classification of MCDM approaches. Various comparison studies have been provided in scientific studies. Brown, *et al.*[15] presented an analysis of several similarity metrics that suggested logic-based (additive) measures as suitable operational decisions. Guitoni and Martel[16] provided an operational method for determining which MCDM technique is best for a given decision-making circumstance. A comparison of MCDM approaches can be used to make the decision. Zanakis, *et al.*[17] tested the eight MCDM approaches, including SAW, ELECTRE, and Multiplicative Exponential Weighting (MEW), and found that MEW and SAW achieved the best results. The outcome of the evaluation is dependent on both the choice of the utility function and its parameters, according to computations in many cases. The taxonomy of MCDM approaches to rendering the information type may be done in a variety of ways. One of the groups can be used to classify approaches based on quantitative measures and systems based on multicriteria utility theory.

The MCDM techniques have been gainfully important in solving decision issues which entail many criteria, these being in most cases conflicting. Such approaches can be utilized especially in the area of strategic planning, like infrastructure development, economic evaluation, and resource allocation, where quantitative and qualitative variables are to be considered on a structured basis. Biswas, *et al.*[24] in their study of infrastructure planning in an institutional environment by use of MCDM-based strategy involving a girls' hostel in a university campus have outlined how MCDM techniques can be applied to optimization of placing facilities. The research study integrated a list of clear-cut criterion-including accessibility, safety, the vicinity around academic buildings, the availability of utilities, and environmental factors, to compare and prioritize the possible sites that can be used in building a girls' hostel.

The methods, such as AHP and TOPSIS, were integrated to give way to subjective preference aggregation and objective decision-making. The paper indicated how it is possible to improve the decision-making process of spatial planning within the university setting using MCDM approaches, which would offer a clear and repeatable process of stakeholder engagement. Likewise, to a multi-criteria ranking of the Balkan countries by the index of economic freedom, the paper by Puška, *et al.*[25] developed a new MCDM-based ranking model to rank the countries.

This paper concentrated on assessing and comparing economic performance and governmental arrangements of the Balkan nations by creating a composite index based on sub-indicators, including the property rights, freedom of trade, health of fiscal systems, and integrity in government. Fuzzy logic and hybrid weighting approaches, which were employed, allowed the model to accommodate uncertainties and vaguenesses that characterise socio-political data. The comparative ranking method was not only indicative of the financial status of the respective country, but it also made forthcoming suggestions on how to make policy decisions and regional development strategies.

3. METHODOLOGY

A pair of approaches is suggested in this section for decision-making scenarios: the SWI method and the SWEI method. Both approaches are thoroughly described in the subsection that follows.

3.1 Concepts of Information Measures

In the context of information theory, an information measure is a method of quantifying the quantity of information included in a message or an event. Information theory is an applied mathematics field that studies information, communication, and data transfer. It offers a rigorous framework for measuring and analyzing the level of ambiguity or surprise connected with various events or messages. The "bit," which represents the basic unit of information, is the fundamental idea in information theory. A bit can have one of two values: 0 or 1.

The goal of information measurements is to express the quantity of information in bits or other relevant units. Communication systems, cryptography, data compression, error correction, machine learning, and computational intelligence are all uses of information theory. The study of Dwivedi and Sharma[19] provides a 'useful' Renyi information rate in terms of information measure. The study conducted by Khan[30], *et al.* investigates threats to data states in data loss prevention using the concept of complex linear Diophantine fuzzy relations.

In information theory, there is a direct relation between the amount of information conveyed by an event or outcome and its probability. Specifically, more information is associated with less probable events, and less information is associated with more probable events. Here is a simple way to understand this concept:

3.1.1 High Information, Low Probability

When an event is improbable or rare, it is more surprising and carries a higher amount of information. These events stand out precisely because they are unexpected. For instance, a total solar eclipse occurring in a specific location is a rare event and conveys a significant amount of information when it happens.

3.1.2 Low Information, High Probability

On the other hand, when an event is highly probable, it means that it is expected and not surprising. In such cases, the event carries very little new information because it was already anticipated. For example, the sun rising in the east each morning is highly probable and does not provide much new information.

This relationship is formalized by Claude Shannon's entropy formula, which measures the information content of a random variable or event. The entropy increases as the probability of an event decreases, indicating that rarer or less probable events carry more information.

In summary, in the context of information theory, events with a higher probability are associated with lower information content because they are less surprising, while events with a lower probability are associated with higher information content because they are more unexpected. This fundamental principle underpins the quantification of information and is widely applicable in fields such as communication, statistics, and decision theory.

According to information theory, information decreases uncertainty (also known as entropy). The increase in likelihood upon message receipt serves as the unit of information measurement. We obtain the quantity of information (bits) in the sense of Shannon's entropy theorem[20], if we accept the A information that we may anticipate with the probability $P(A)$, then it can be expressed in the amount of information by $I(A)$ as follows:

$$I(A) = \log_2\left(\frac{1}{P(A)}\right)$$

If we use Shannon's theorem to quantify the amount of information, $I(A)$ will be true. For example, $A_1, A_2, A_3 \ldots\ldots A_9$ are the set of 9 alternatives and let their probabilities of coming first rank be 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9, respectively. Then the amount of information for these probabilities will be 3.332, 2.322, 1.737, 1.322, 1.000, 0.737, 0.515, 0.322, and 0.152, respectively. For the alternatives, the relationship between probability and the amount of information is illustrated in Fig. 1. It can also be seen from Fig. 1 that when the amount of information about an

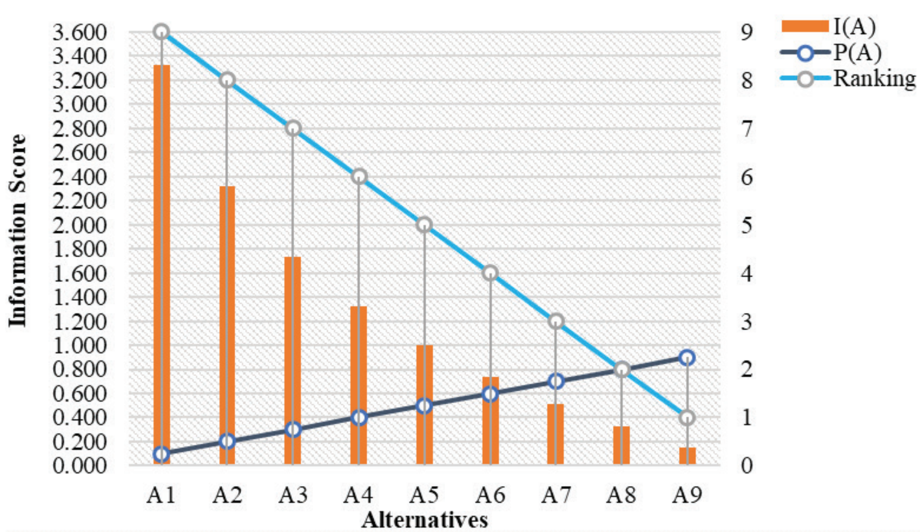

Figure 1. The relation between probability and the amount of information.

Table 1. The relation between probability and the amount of information

Criteria → Alternative ↓	C_1 Max or Min	C_2 Max or Min	C_3 Max or Min	…	C_n Max or Min
A_1	$\overline{IDM}_{1,1}$	$\overline{IDM}_{1,2}$	$\overline{IDM}_{1,3}$	…	$\overline{IDM}_{1,n}$
A_2	$\overline{IDM}_{2,1}$	$\overline{IDM}_{2,2}$	$\overline{IDM}_{2,3}$	…	$\overline{IDM}_{2,n}$
A_3	$\overline{IDM}_{3,1}$	$\overline{IDM}_{3,2}$	$\overline{IDM}_{3,3}$	…	$\overline{IDM}_{3,n}$
…	…	…	…	…	…
A_m	$\overline{IDM}_{m,1}$	$\overline{IDM}_{m,2}$	$\overline{IDM}_{m,3}$	…	$\overline{IDM}_{m,n}$
Sum	$\sum_{i=1}^{m} \overline{IDM}_{i,1} = 1$	$\sum_{i=1}^{m} \overline{IDM}_{i,2} = 1$	$\sum_{i=1}^{m} \overline{IDM}_{i,3} = 1$	…	$\sum_{i=1}^{m} \overline{IDM}_{i,j} = 1$

alternative increases, the probability of that alternative coming first decreases; similarly, as the amount of information about an alternative decreases then the probability of that alternative coming first increases.

3.2 New Algorithm

In this section, we propose two new multicriteria decision-making methods, SWI and SWEI. These are the new methods in the existing literature; these may also be known as Decision Making by Information Measure (DMIM) methods in multi-criteria tactics. These algorithms can be applied to all decision-making challenges with their criteria. The method can become better and be used in MCDM problems. In the context of information theory, events with a higher probability are associated with lower information content because they are less surprising, while events with a lower probability are associated with higher information content because they are more unexpected. This fundamental principle underpins the quantification of information and is widely applicable in fields such as communication, statistics, and decision theory. We are using this principle in multicriteria decision-making.

3.3 Sum-Weighted Information

The SWI method can arguably be the most practical, particularly for issues that only have one dimension. The best alternative is the one that meets the expression given if there are *m* alternatives and *n* criteria. The Sum Weighted Information will be the name of the governing assumption for this model. Mainly in the Sum Weighted Information, each alternative is measured for each criterion in its logarithmic value with base 2 by multiplication with the weight of the criteria, which means each normalized value of the information matrix is multiplied by the corresponding criterion's relative weight. The amount of information was measured in bits (binary digits). Later, all the information is added as sum-weighted information. In other words, the sum-weighted information is provided as the sum of all information for each criterion. The SWI can be utilized with ease in single-dimensional scenarios when all the units are identical (for example, dollars, feet, and seconds). When used to solve multi-dimensional decision-making problems, this strategy has limitations. The additive utility premise is thus invalidated by incorporating multiple aspects, and as a result, different units. The process SWI method involves the following steps:

3.3.1 Step 1

To solve the MCDM problem, the decision-maker develops the information decision matrix (IDM) in the first stage:

$$IDM_{i,j} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{bmatrix} \tag{1}$$

In the second stage, the Information Matrix assigns the criterion in particular values of the matrix where the alternatives are scored based on the criteria shown in (1), For the beneficial criteria, we will use (2), and for the non-beneficial criteria, we will use (3) and the values are normalized as follows:

$$\overline{IDM}_{i,j} = \frac{a_{i,j}}{\sum_{i=1}^{m} a_{i,j}} \tag{2}$$

$$\overline{IDM}_{i,j} = \frac{1/a_{i,j}}{\sum_{i=1}^{m} 1/a_{i,j}} \tag{3}$$

The value $\overline{IDM}_{i,j}$ shows the probability of each attribute of i^{th} alternative in the j^{th} the criterion, where the sum of all probabilities of each alternative for the criteria will be 1, i.e., $\sum_{i=1}^{m} \overline{IDM}_{i,j} = 1$ where, i=1,2,…m (alternative rows) and j=1,2,…n (alternative coloumns). Table 1 represents a more generalization of $\overline{IDM}_{i,j}$ for criteria.

3.3.2 Step 2

In this step, using the previously determined SWI, the total amount of information for each possibility is computed independently.

For example, if we want to calculate the amount of information for the first alternative A_1 with corresponding attributes $a_{1,1}, a_{1,2}, a_{1,3} \ldots a_{1,n}$ in a decision matrix $IDM_{i,j}$, where i=1,2,3,…n alternative and j=1,2,3,…n criteria with the probability distribution $\overline{IDM}_{1,1}, \overline{IDM}_{1,2}, \ldots \overline{IDM}_{1,n}$ and the corresponding criteria weight $w_1, w_2, w_3 \ldots w_n$.

This might be denoted as IDM'_1 and define it as follows:

$$IDM'_1 = w_1 \log_2\left(\frac{1}{\overline{IDM}_{1,1}}\right) + \cdots + w_n \log_2\left(\frac{1}{\overline{IDM}_{1,n}}\right)$$

Similarly, the amount of information for the remaining alternatives can be calculated as:

$$IDM'_2 = w_1 \log_2\left(\frac{1}{\overline{IDM}_{2,1}}\right) + \cdots + w_n \log_2\left(\frac{1}{\overline{IDM}_{2,n}}\right)$$

……………………………………….

$$IDM'_m = w_1 \log_2\left(\frac{1}{\overline{IDM}_{m,1}}\right) + \cdots + w_n \log_2\left(\frac{1}{\overline{IDM}_{m,n}}\right)$$

Finally, the generalized amount of information for i alternatives is denoted by IDM_1' and it can be written as the following Eqn. (4):

$$SWI = IDM_i' = \sum_{j=1}^{n} w_j \log_2\left(\frac{1}{\overline{IDM}_{i,j}}\right) \quad (4)$$

3.4 Sum-Weighted Exponential Information

The SWEI method is different from the SWI model. The major distinction is that, as a substitute for the addition-weighted in the model, there is an exponential-criterion weight. Each alternative is measured for each criterion in its logarithmic value with base 2 by exponential weight. And later, all the information is added as sum-weighted-exponential information. This means each normalized value of the information matrix is raised to a power equal to the relative weight of the corresponding criterion. Therefore, in general, measuring the information of the alternatives can be calculated. Both single- and multi-dimensional decision-making issues can be solved using the SWEI. Bits are the units used to quantify information (binary digits). This method's advantage of employing relative values rather than exact values is a benefit. This is especially important in sectors such as data compression, where understanding the expansion of information as the number of potential symbols or messages rises is critical for effective coding and compression techniques.

The process of the SWEI method involves the following steps:

- The first step is the same as the SWI
- The second step is the same as the SWI
- The total amount of information for each alternative is computed individually based on the SWEI method outlined earlier.

For example, if we want to calculate the amount of information by the SWEI method for the first alternative A_1 with corresponding attributes $a_{1,1}, a_{1,2}, a_{1,3} \ldots a_{1,n}$ in an information decision matrix $\overline{IDM_{i,j}}$ with the probability distribution $\overline{IDM}_{1,1}, \overline{IDM}_{1,2}, \overline{IDM}_{1,3} \ldots \overline{IDM}_{1,n}$ and the corresponding criteria weight $w_1, w_2, w_3 \ldots w_n$. This might be denoted as IDM_1'' and define it as follows:

$$IDM_1'' = \left(\log_2\left(\frac{1}{\overline{IDM}_{1,1}}\right)\right)^{w_1} + \cdots + \left(\log_2\left(\frac{1}{\overline{IDM}_{1,n}}\right)\right)^{w_n}$$

Similarly, the amount of information for the remaining alternatives can be calculated as:

$$IDM_2'' = \left(\log_2\left(\frac{1}{\overline{IDM}_{2,1}}\right)\right)^{w_1} + \cdots + \left(\log_2\left(\frac{1}{\overline{IDM}_{2,n}}\right)\right)^{w_n}$$

$$\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

$$IDM_m'' = \left(\log_2\left(\frac{1}{\overline{IDM}_{m,1}}\right)\right)^{w_1} + \cdots + \left(\log_2\left(\frac{1}{\overline{IDM}_{m,n}}\right)\right)^{w_n}$$

Finally, the generalized amount of information for i alternatives is denoted by IDM_i'' and it can be written as the following Eqn. (5):

$$SWEI = IDM_i'' = \sum_{j=1}^{n} \left(\log_2\left(\frac{1}{\overline{IDM}_{i,j}}\right)\right)^{w_j} \quad (5)$$

Here, a base-2 logarithm in Eqn. (4) and Eqn. (5) has a logarithm was chosen because bits (binary digits) are used to measure the amount of information for attributes and i=1,2,…m and j=1,2,…n. In terms of information processing, this can be immediately translated as the number of bits needed to express the criteria. After measuring the information from (4) and (5), the calculated amount of information will be arranged in descending order of the received amount of information. The main reason for taking it in descending order is that a higher amount of information about an alternative gives a lower probability of that alternative; this means that the chances of that alternative coming first are slim to none. And less amount of information about any alternatives provides a higher probability of that alternative, which means that the alternative is most likely to come first. In Eqn. (4) and Eqn. (5), w_j is the weight of the j^{th} criterion. The smallest amount of information (IDM_1') and (IDM_1'') is the best choice because the value of the normalized data is closer to zero. The process of the SWI and SWEI methods is demonstrated in Fig. 2.

3.4 The Entropy Method

Shannon's entropy plays a pivotal role in MCDM by providing a quantitative framework for managing uncertainty and information. It is utilized to determine the weights of criteria, ensuring that decision-makers can prioritize effectively based on objective measures of uncertainty. Additionally, entropy quantifies the information content of alternatives and criteria, which is essential for developing robust decision-making models that can handle complex and uncertain data. This approach also aids in modeling decision-making under uncertainty, allowing for informed choices despite the inherent unpredictability of the data. For example, a study by[31] has applied the Entropy method combined with fuzzy VIKOR in the selection of a supplier. The study by[26] combined the Entropy method and the Fuzzy Comprehensive method to evaluate the operational capability of the data fabric solution selection. The Entropy method can be summarized in 5 steps[27-29]:

Step 1: As the first stage, a decision matrix (DM) containing criteria and alternatives is created, according to (1).

Step 2: The values of the decision matrix are normalized with the help of Eqn. (6). The $s_{i,j}$ value in Eqn. (6) shows the normalized value.

$$s_{i,j} = \frac{a_{i,j}}{\sum_{i=1}^{m} a_{i,j}} \quad (6)$$

Step 3: After the normalization process, the entropy value of each criterion is obtained using Eqn. (7). The value of H_j in the Eqn. shown below represents the entropy of the jj criterion.

$$H_j = -\frac{\sum_{j=1}^{n} s_{i,j} \log_2 s_{i,j}}{\log_2 m} \quad (7)$$

Step 4: In the last step, the weight of each criterion is obtained with the help of Eqn. (8).

$$w_j = \frac{1-H_j}{\sum_{j=1}^{n} 1-H_j} \quad (8)$$

The value of w_j in Eqn. (8) represents the objective weight of the criterion is represented. Through the application of the entropy method, these objective criterion weights are determined.

3.5 The MOORA Method

The Multi-Objective Optimization Method by Ratio Analysis (MOORA) is a part of the initial introduction given by Brauers and Zavadskas[31] in the early 2000s; the method emerged as a strong and step-wise methodology of finding or resolving an intricate MCDM problem. A notable early use of MOORA was suggested in 2004 by Brauers and Zavadskas as an advance on the classical ratio-based approaches to decision-making, and especially as applicable to decision situations where both benefit- and cost-type measures are to be considered. There is a possibility of employing its use in determining the most suitable alternative, which is assessed by some criteria that are considered favourable and/or unfavorable[32].

The application of the MOORA method includes three basic steps:

Step 1: As the first stage, a decision matrix (DM) containing criteria and alternatives is created, according to (1).

Step 2: The values of the decision matrix are normalized according to (9) using vector normalization.

$$v_{i,j} \frac{a_{i,j}}{\sqrt{\sum_{i=1}^{m} a_{i,j}^2}} \tag{9}$$

Step 3: The MOORA score for each alternative is measured by the following Eqn.:

$$y_i^* = \sum_{j=1}^{t} w_j v_{i,j} - \sum_{j=t+1}^{n} w_j v_{i,j} \tag{10}$$

where w_j is the weight of the i alternative for j=1,2….t and j=t+1, t+2…n criterion.

In the final ranking, alternatives with higher scores are considered more favorable. The alternative with the highest score is identified as the optimal choice, whereas the one with the lowest score is regarded as the least desirable.

4. APPLICATION

We identify the top arc welding robots in this section. Table 2 displays an information decision matrix based on various selection criteria for arc welding robots and the source of the data taken from the study [21]. The data on the eight robots of arc welding was collected using the following five criteria: average power consumption (C-1) unit k.w., mechanical weight (C-2) unit kg, payload (C-3) unit kg, repeatability (C-4), unit (+/-) mm, maximum reach (C-5) unit mm. The information decision matrix is shown in Table 2. Indicators for maximum ('Max') advantageous criteria and minimal ('MIN') cost criteria were indicated by the improvement optimization.

The robot's power consumption, for example, falls within the non-beneficial criteria (a lower value is desirable for the minimization problem). Criteria play an important role in the selection of any arc welding robot, such as weld quality, material compatibility, safety and environmental considerations, productivity and efficiency, mechanical weight, cost, payload capacity, industry standards and regulations, future flexibility, etc. In this study, the following five important criteria were considered while choosing an arc welding robot:

- The robot's average power usage in kilowatts (C-1): This relates to the average power units utilized by the robot. It is a non-beneficial condition because it is often desired for a robot to consume less electricity
- Robot's mechanical weight in kilograms (C-2): It is a non-beneficial criterion since buyers often prefer lighter robots, which relates to the physical weight of the robot
- The robotic payload in kilograms (C-3): This refers to the entire weight an automated device can lift in a single

Table 2. Information Decision Matrix (IDM) for arc welding robots.

Robots ↓ criteria →	**C-1 Min**	**C-2 Min**	**C-3 Max**	**C-4 Max**	**C-5 MAX**
Robo-1	1	145	12	0.02	1441
Robo-2	0.5	27	7	0.018	911
Robo-3	0.6	170	4	0.05	1500
Robo-4	3.4	272	20	0.04	1650
Robo-5	2	250	25	0.02	2409
Robo-6	5.6	230	10	0.05	1925
Robo-7	2.5	105	6	0.15	4368
Robo-8	5.05	215	8	0.08	1801

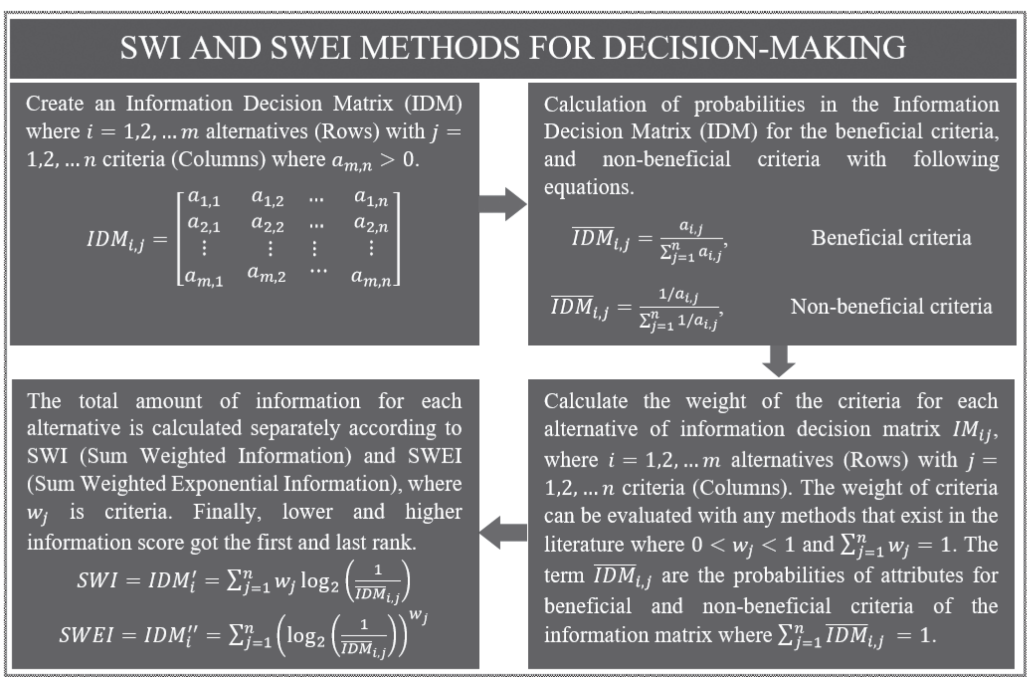

Figure 2. Conceptual model of SWI and SWEI MCDM.

revolution. It is a beneficial criterion because it is often preferred to be more

- Repeatability in millimeters (C-4): This term describes the robot's capacity to repeat a given job repeatedly. Repeatability is a beneficial criterion since it is often regarded to be higher
- Maximum reach in millimeters (C-5): It is the average of the maximum horizontal and vertical distance to which a robot can extend its arms to do the task. It is a beneficial criterion because it is typically desirable to be higher.

4.1 Entropy Method for Weight Calculation

To calculate the weight of the criterion, we apply Shannon's entropy method for generating the objective criteria weights[20]. Dwivedi and Sharma[18,22-23] used Shannon's entropy approach to derive the objective weight in the present work. Figure 3 represents the variation of the criterion weights. It is clear from Shannon's entropy that the weights of the criteria are respectively. We calculate the weight of the criterion, such as w_1=0.291 for average power consumption, w_2=0.130 for mechanical weight, w_3=0.182 for payload, w_4=0.283 for repeatability, and w_5=0.114 for maximum reach. The sum of all these weights is one, which satisfies the condition of the criterion weight i.e., $\sum_{j=1}^{n} w_j = 1$, where $0<w_j<1$.

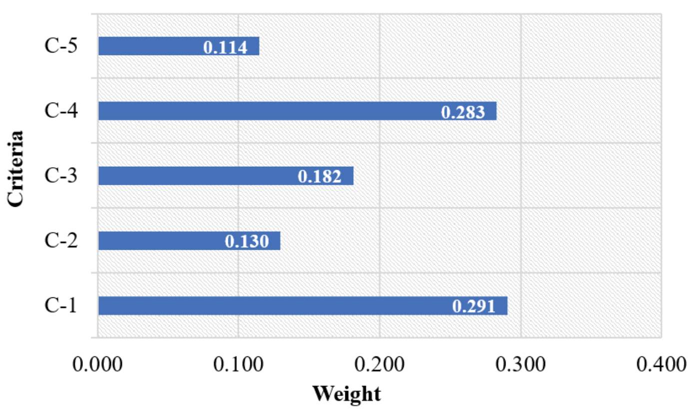

Figure 3. Entropy criterion weight variation.

4.2 Alternative Ranking by SWI and SWEI

In this part, we rank the alternatives by normalizing the original decision matrix using Eqn. (2) and Eqn. (3) for the benefit and cost criteria, respectively. In addition, the C-1 and C-2 criteria are cost criteria (lower value better), whilst the others are benefit criteria (higher value better). The criterion weights are then used in the SWI and SWEI techniques to produce ranking results that are compatible with the methodology. The normalized values of the information decision matrix, which is the first stage of the proposed technique, are shown in Table 3. For example, the normalized value first robot, Robo-1, for the attributes $a_{1,1}, a_{1,2}, \ldots a_{1,5}$ can be calculated for cost and benefit criteria as follows:

$$\overline{IDM}_{i,j} = \frac{1/a_{i,j}}{\sum_{i=1}^{m} 1/a_{i,j}}$$

$$\overline{IDM}_{1,1} = \frac{1/1}{1+1/0.5+1/0.6+1/3.4+1/2+1/5.6+1/2.5+1/5.05}$$

$$\overline{IDM}_{i,j} = \frac{1/a_{i,j}}{\sum_{i=1}^{m} 1/a_{i,j}}$$

$$\overline{IDM}_{1,1} = \frac{1/1}{1+1/0.5+1/0.6+1/3.4+1/2+1/5.6+1/2.5+1/5.05}$$

$$\overline{IDM}_{1,1} = \frac{1}{1+2+1.667+0.294+0.500+0.179+0.400+0.198}$$

$$\overline{IDM}_{1,1} = \frac{1}{6.238} = 0.160$$

$$\overline{IDM}_{1,2} = \frac{1/145}{1/145+1/27+1/170+1/272+1/250+1/230+1/105+1/215}$$

$$\overline{IDM}_{1,2} = \frac{0.007}{0.007+0.037+0.006+0.004+0.004+0.010+0.005}$$

$$\overline{IDM}_{1,2} = \frac{0.007}{0.076} = 0.091$$

Similarly, for beneficial criteria can be calculated by

$$\overline{IDM}_{i,j} = \frac{a_{i,j}}{\sum_{i=1}^{m} a_{i,j}}$$

$$\overline{IDM}_{1,3} = \frac{12}{12+7+4+20+25+10+6+8} = \frac{12}{92}$$

$$\overline{IDM}_{1,3} = 0.130$$

$$\overline{IDM}_{1,4} = \frac{0.02}{0.02+0.02+0.05+0.04+0.02+0.05+0.015+0.08}$$

$$\overline{IDM}_{1,4} = \frac{0.02}{0.430} = 0.047$$

$$\overline{IDM}_{1,5} = \frac{1441}{1441+911+1500+1650+2409+1925+4368+1801}$$

$$\overline{IDM}_{1,5} = \frac{1441}{16005} = 0.090$$

Similarly, other attributes for the remaining alternatives have been calculated accordingly. The calculated value has been tabulated in Table 3.

After calculating the normalized value for the alternative, applying (4) and (5) to calculate the information score for SWI and SWEI MCDM, respectively. Here we calculate the information score for these two methods one by one. Firstly, we calculate the information score for 1st alternative by SWI MCDM as follows:

$$IDM_i' = \sum_{j=1}^{n} w_j \log_2\left(\frac{1}{\overline{IDM}_{i,j}}\right)$$

$$IDM_1' = \sum_{j=1}^{5} w_j \log_2\left(\frac{1}{\overline{IDM}_{i,j}}\right) = w_1 \log_2\left(\frac{1}{\overline{IDM}_{1,1}}\right) + w_2 \log_2\left(\frac{1}{\overline{IDM}_{1,2}}\right) + \ldots + w_5 \log_2\left(\frac{1}{\overline{IDM}_{1,5}}\right)$$

$$IDM_1' = 0.291 \times \log_2\left(\frac{1}{0.160}\right) + 0.130 \times$$

$$\log_2\left(\frac{1}{0.091}\right) + 0.182 \times \log_2\left(\frac{1}{0.130}\right) + 0.283 \times \log_2\left(\frac{1}{0.047}\right) + 0.114 \times \log_2\left(\frac{1}{0.090}\right)$$

$$IDM'_1 = 0.291 \times 2.641 + 0.130 \times 3.462 + 0.182 \times 2.639 + 0.283 \times 4.426 + 0.114 \times 3.473$$

$$IDM'_1 = 0.768 + 0.450 + 0.533 + 1.251 + 0.398$$

$$IDM'_1 = 3.401 \text{ bits.}$$

$$IDM''_i = \sum_{j=1}^{n} \left(\log_2\left(\frac{1}{IDM_{i,j}}\right)\right)^{w_j}$$

$$IDM''_1 = \sum_{j=1}^{5} w_j \log_2\left(\frac{1}{IDM_{i,j}}\right) = \left(\log_2\left(\frac{1}{IDM_{1,1}}\right)\right)^{w_1} + \left(\log_2\left(\frac{1}{IDM_{1,2}}\right)\right)^{w_2} + \ldots + \left(\log_2\left(\frac{1}{IDM_{1,5}}\right)\right)^{w_5}$$

$$IDM''_1 = \left(\log_2\left(\frac{1}{0.160}\right)\right)^{0.291} + \left(\log_2\left(\frac{1}{0.091}\right)\right)^{0.130} + \left(\log_2\left(\frac{1}{0.130}\right)\right)^{0.182} + \left(\log_2\left(\frac{1}{0.047}\right)\right)^{0.283} + \left(\log_2\left(\frac{1}{0.090}\right)\right)^{0.114}$$

$$IDM''_1 = (2.641)^{0.291} + (3.462)^{0.130} + (2.639)^{0.182} + (4.426)^{0.283} + (3.473)^{0.114}$$

$$IDM''_1 = 1.327 + 1.175 + 1.216 + 1.523 + 1.153$$

$$IDM''_1 = 6.394 \text{ bits.}$$

Table 3. Normalize Decision Matrix (NDM) for cost criteria and benefit criteria

Robots ↓ criteria →	C-1 Min	C-2 Min	C-3 Max	C-4 Max	C-5 Max
Robo-1	0.160	0.091	0.130	0.047	0.090
Robo-2	0.321	0.487	0.076	0.042	0.057
Robo-3	0.267	0.077	0.043	0.117	0.094
Robo-4	0.047	0.048	0.217	0.093	0.103
Robo-5	0.080	0.053	0.272	0.047	0.151
Robo-6	0.029	0.057	0.109	0.117	0.120
Robo-7	0.064	0.125	0.065	0.350	0.273
Robo-8	0.032	0.061	0.087	0.187	0.113

After normalizing the decision matrix, we calculate the sum-weighted information by (4) and the sum-weighted exponential information by (5) based on the information provided regarding the factors describing the arc welding Robots. Table 4 shows the sum-weighted information and the sum-weighted exponential information, respectively. After measuring the amount of information, we ranked the arc welding Robots in descending order.

Upon examining the eight robots based on five criteria—average power usage, mechanical weight, robotic payload, repeatability, and maximum reach—the rankings revealed an unexpected outcome. This suggests that Robo-7 excelled in balancing the evaluated parameters effectively, potentially optimizing functionality in ways beyond raw data metrics. According to the results from Table 4, the amount of information of Robot-7 is 2.900 bits of information by SWI and 6.127 bits of information by SWEI, respectively. Similarly, Robot-6 has obtained 3.836 bits of information and 6.560 bits of information through SWI and SWEI methods, respectively, which is more than Robot-7. Hence, Robo-7 got the first rank, and Robot-6 was placed last in the list of robots.

This could imply inefficiencies or trade-offs in its design that prioritize certain attributes, like payload capacity or reach, at the expense of other critical factors such as power usage or repeatability. Therefore, the robots taken in this study can be grouped according to the information obtained using SWI and SWEI methods in arc welding machinery and may be ranked from first to last as follows: Robo-7 > Robo-2 > Robo-3 > Robo-1 > Robo-5 > Robo-4 > Robo-8 > Robo-6. The ranking of these alternatives may be seen in Fig. 4. The rankings highlight the importance of holistic performance rather than isolated strengths. Evaluating robots on multiple criteria enables nuanced assessments, ensuring that the best-performing robot aligns with practical, balanced operational demands rather than simply maximizing specific metrics.

4.3 Sensitivity Analysis

A fair and impartial evaluation of the options is guaranteed by the equal weight method's validation of results for robot selection in the defence industry within the MCDM area. By recognizing each evaluation criterion as equally important in the decision-making process, the equal weight method gives them all the same weight. This method offers a solid foundation for comparison and sheds light on the consistency and fairness of the selection results. The equal weight technique enables an unbiased aggregation of performance across various variables,

Table 4. Ranking of arc welding robots by SWI and SWEI methods

Robots ↓ criteria →	C-1 Min	C-2 Min	C-3 Max	C-4 Max	C-5 Max	SWI Score	Rank	SWEI score	Rank
Robo-1	0.768	0.450	0.533	1.251	0.398	3.401	**4**	6.394	**4**
Robo-2	0.477	0.135	0.675	1.294	0.473	3.055	**2**	6.143	**2**
Robo-3	0.554	0.479	0.821	0.877	0.391	3.123	**3**	6.234	**3**
Robo-4	1.282	0.567	0.400	0.968	0.375	3.593	**6**	6.467	**6**
Robo-5	1.059	0.552	0.341	1.251	0.313	3.516	**5**	6.430	**5**
Robo-6	1.492	0.536	0.581	0.877	0.350	3.836	**8**	6.560	**8**
Robo-7	1.153	0.389	0.715	0.428	0.214	2.900	**1**	6.127	**1**
Robo-8	1.448	0.523	0.640	0.685	0.361	3.657	**7**	6.475	**7**

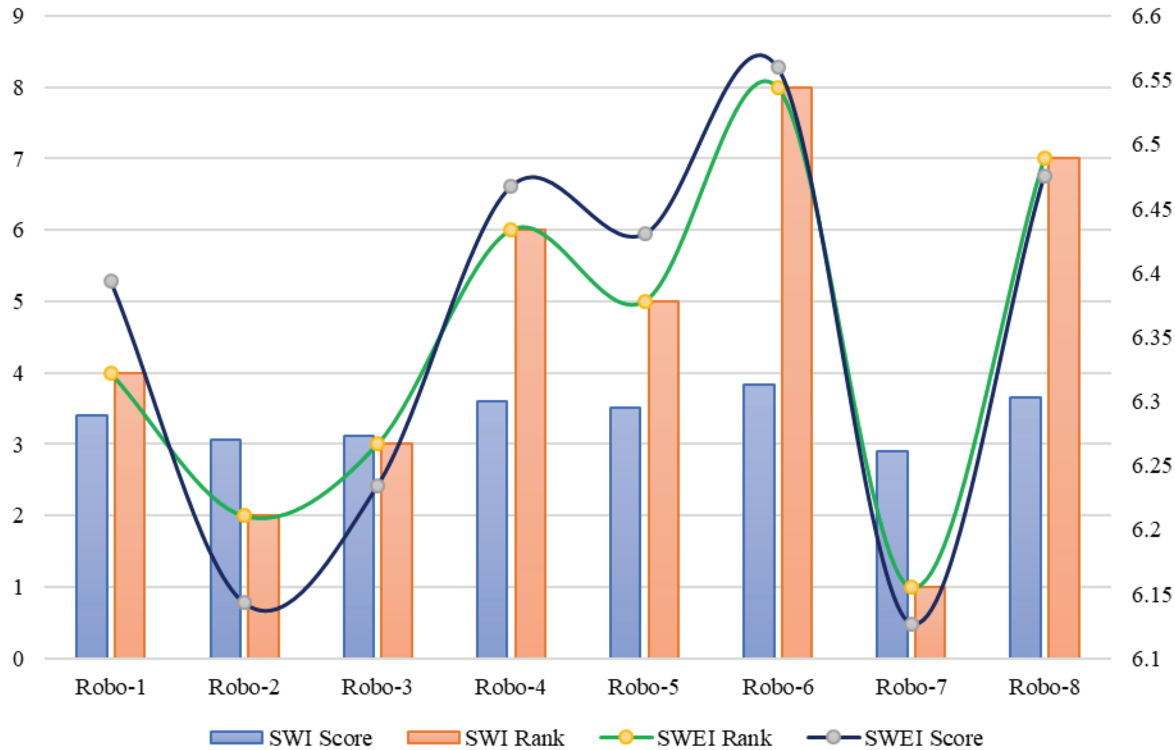

Figure 4. Ranking illustration of arc welding robots by SWI and SWEI methods.

including power consumption, payload capacity, mechanical weight, repeatability, and maximum reach, which are all examined in the defence industry. To ensure a fair comparison, each criterion is normalized to remove the impact of different scales or units. The scores for each robot are then aggregated to compute an overall performance index.

By employing this equal weight technique, the validation procedure confirms if the robot that was first chosen matches the one that is ranked highest when all criteria are given equal weight. Potential biases in the weighting or prioritization of criteria during the first analysis may be indicated if the equal-weight method results show a considerable difference from the primary decision-making results. On the other hand, comparable outcomes demonstrate how sound the decision-making process was and validate that the chosen robot is a well-rounded option that can satisfy defensive specifications.

Furthermore, the equal weight technique emphasizes the trade-offs between criteria, determining if particular robots thrive in specific domains while underperforming in others.

This allows decision-makers to guarantee that the selected robot performs consistently across all relevant metrics. Finally, confirming findings using the equal weight technique lends legitimacy to the decision-making process, guaranteeing that the best robot is chosen for defensive applications.

The five criteria—power consumption, mechanical weight, payload capacity, repeatability, and maximum reach—were given equal weight to guarantee the validity of the robot selection procedure. This approach offered an objective baseline for comparison by giving each criterion the same weight. All of the robots' normalized scores were combined to provide a thorough assessment. The reliability of the chosen robot and the consistency of the decision-making process were confirmed by comparing the outcomes of this method with the initial rankings. We are taking the weight as follows:

$$W_{power\ consumption} = W_{mechanical\ weight} = W_{payload\ capacity} = W_{repeatability} = W_{maximum\ reach} = 0.200$$

The validity of the proposed methods, SWI and SWEI,

Table 5. Ranking comparison by equal weight and entropy weight method

Alternative robots	Entropy weight approach			Equal weight approach		
	SWI score	SWEI score	Ranking	SWI score	SWEI score	Ranking
Robo-1	3.401	6.394	4	3.387	6.366	5
Robo-2	3.055	6.143	2	3.020	6.098	2
Robo-3	3.123	6.234	3	3.326	6.321	3
Robo-4	3.593	6.467	6	3.535	6.406	6
Robo-5	3.516	6.430	5	3.384	6.334	4
Robo-6	3.836	6.560	8	3.722	6.481	8
Robo-7	2.900	6.127	1	2.857	6.095	1
Robo-8	3.657	6.475	7	3.621	6.438	7

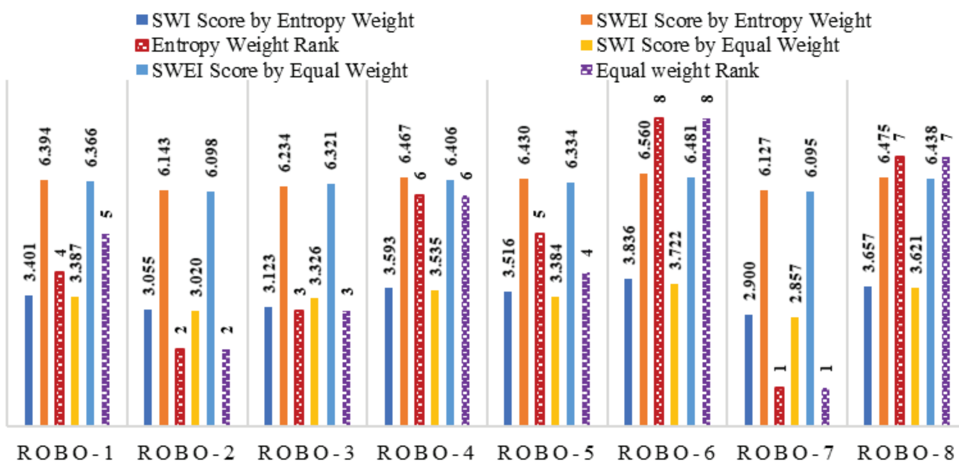

Figure 5. Ranking the robots with the entropy and equal weight method.

will be checked using Eqn. (4) and Eqn. (5), respectively. Table 5 shows the information scores and ranking for the proposed SWI and SWEI methods with equal weights and entropy weights for the criteria. We give a bar graph in Fig. 5, which represents the comparative information scores of the alternative robots in a visual format. This visualization helps to quickly identify top performers among the ranked items.

4.4 Ranking Comparison by MOORA MCDM

In this subsection, we compare the robustness of the ranking of the proposed methods with the MOORA MCDM method. Firstly, the decision matrix is constructed for MOORA MCDM according to (1), in the first step from the raw data shown in Table 2. In the second step, the data is normalized using (9). Finally, in the third step, calculate the final score of each alternative by (10) and rank the alternatives in descending order. The alternative with the highest score is identified as the optimal choice, whereas the one with the lowest score is regarded as the least desirable. Table 6 shows the ranking comparison of SWI and SWEI by MOORA MCDM with the entropy weighting method. Figure 6 provides a comparison of the ranking results.

The ranking results presented in Table 6 indicate that Robo-7 consistently achieved the 1st rank across all evaluation methods. Robo-2 secured the 2nd position under the proposed method, while it attained the 4th rank using the MOORA method. Robo-3 was ranked 3rd by both the SWI and SWEI methods, as well as by the MOORA method. Robo-1 was placed 4th by the SWI and SWEI methods, while it received the 5th position according to the MOORA method. Robo-5 occupied the 5th position in both the proposed methods, while it achieved the 2nd position using the MOORA method. Robo-4 and Robo-8 were ranked 6th and 7th, respectively, across all three methods with the same entropy weights. Finally, Robo-6 consistently received the 8th (last) rank across all methods, regardless of the weighting strategy.

Table 6. Ranking by the SWI and SWEI method.

Alternative robots	Entropy weight approach				
	SWI score	SWEI score	Ranking	MOORA score	Ranking
Robo-1	3.401	6.394	4	0.046	5
Robo-2	3.055	6.143	2	0.054	4
Robo-3	3.123	6.234	3	0.060	3
Robo-4	3.593	6.467	6	0.010	6
Robo-5	3.516	6.430	5	0.069	2
Robo-6	3.836	6.560	8	-0.080	8
Robo-7	2.900	6.127	1	0.224	1
Robo-8	3.657	6.475	7	-0.026	7

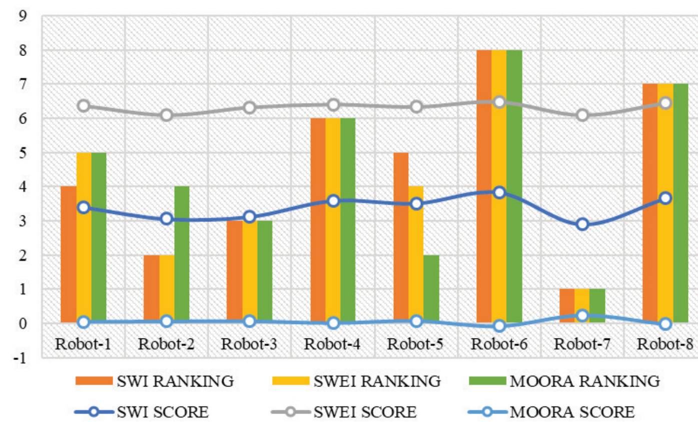

Figure 6. Ranking comparison of SWI and SWEI with the MOORA method.

5. DISCUSSION

The current analysis has shown that Robot-7 is the best alternative out of the eight different robotic welding automated appliances under examination. In addition, the research has ranked several other options, assisting industrial concerns in making decisions based on availability and available resources. By the application of SWI, SWEI, and Entropy MCDM approaches, this study has fundamentally made a substantial addition to the literature on decision-making linked to choosing an industrial arc welding robot and assisted industrial houses in making judgments quickly and easily. Although there is a lot of research work available in the literature related to robot selection, there is no study exists in the literature for robot selection related to information measurement. Therefore, the purpose of this study is to select a robot selection on information measurement.

The evaluation of eight robots using five criteria—average power usage, mechanical weight, robotic payload, repeatability, and maximum robot reach in millimeters—revealed intriguing insights into their performance rankings. Notably, Robot 7 achieved the first rank with a lower information score for these parameters, while Robot 6, with a higher information score, was ranked last. This outcome emphasizes that performance rankings depend not just on individual parameter magnitudes but on the overall balance and suitability for intended applications.

Robot 7's success in securing the top position in entropy weight, as well as equal weight, suggests that it may have achieved an optimal balance among the criteria. For instance, it could possess efficient power usage and a lightweight design, enabling superior repeatability and functionality within a specific operational context. This indicates that its design likely emphasizes practicality and operational efficiency over sheer capacity or reach, demonstrating that raw numbers alone do not determine effectiveness.

The SWI method employs a straightforward linear weighting scheme, providing a transparent mechanism for prioritizing decision criteria. In contrast, the SWEI method applies an exponential weighting function, allowing for more refined differentiation in scenarios that are important for nuanced criteria. Both methods offer flexibility and adaptability, enabling decision-makers to tailor weight adjustments based on specific requirements. To demonstrate the effectiveness and applicability of these methods, an empirical case study in defence systems is presented within the context of robot project selection, a field that demands rigorous MCDM approaches.

Conversely, Robot 6's last-place ranking, despite having higher values, suggests potential design inefficiencies or trade-offs. For example, its larger mechanical weight or excessive power usage may have offset its advantages in payload capacity or reach, making it less suitable for scenarios requiring precision or efficiency. This outcome underscores the importance of considering all criteria collectively rather than focusing on maximizing individual metrics.

The results highlight the significance of tailoring robot designs to specific use cases rather than pursuing one-size-fits-all solutions. The interplay between factors such as power consumption, weight, and reach should align with the operational needs. For decision-makers, this analysis reinforces the need to evaluate robots holistically, considering their ability to meet practical demands rather than relying solely on high performance in isolated criteria. This approach ensures the selection of robots that deliver balanced, effective, and context-appropriate solutions.

Arc welding robots are integral to the defence sector, playing a vital role in manufacturing, maintaining, and repairing critical equipment and structures. These automated systems leverage advanced welding technologies to deliver high precision, consistency, and efficiency, meeting the stringent demands of defence applications.

5.1 Applications of Arc Welding Robots in the Defence Sector

5.1.1 Manufacturing of Military Vehicles and Equipment

5.1.1.1 Armored Vehicles and Tanks

Arc welding robots are used to assemble heavy armor plating and structural components, ensuring welds are robust and defect-free. This enhances the durability and safety of vehicles operating under extreme conditions.

5.1.1.2 Naval Vessels

For ships and submarines, arc welding robots contribute to constructing hulls, bulkheads, and other structural components. They handle complex geometries and high-strength materials required for naval applications.

5.1.2 Construction of Specialized Infrastructure

Defence infrastructure, such as missile silos, radar stations, and protective shelters, relies on strong and precise welding. Arc welding robots ensure these structures meet high standards of safety and resilience.

5.1.3 Weapon Systems Fabrication

Modern weapon systems, including missiles and artillery, involve intricate welding of components made from advanced alloys. Arc welding robots provide the precision and repeatability needed to meet the exacting tolerances required for such systems.

5.1.4 Maintenance and Repair

5.1.4.1 Combat Equipment

Defence equipment faces wear and damage during operation. Arc welding robots are employed for maintenance tasks, such as restoring worn surfaces and repairing damaged components, thereby extending equipment lifespan.

5.1.4.2 Naval and Aerospace Repair

These robots are particularly valuable for repairing ships and aircraft, where downtime needs to be minimized. They perform complex welds in confined spaces with speed and accuracy.

5.1.5 Prototype Development and Testing

- Arc welding robots are instrumental in developing prototypes for new defence technologies. Their ability to produce consistent welds allows researchers to test designs reliably and iterate quickly
- Prototypes for advanced weaponry, vehicles, and aerospace components often require welding of exotic materials, a task robots excel in.

5.2 Advantages of Arc Welding Robots in Defence

5.2.1 Precision and Repeatability

Robots consistently deliver high-quality welds, reducing the likelihood of defects that could compromise safety or performance.

5.2.2 Enhanced Productivity

Robots operate continuously at high speeds, reducing production timelines for critical defence projects.

5.2.3 Safety for Human Workers

Automating welding tasks in hazardous environments minimizes exposure to risks such as intense heat, sparks, and toxic fumes.

5.2.4 Cost-Effectiveness

Despite high initial costs, robots' lower long-term expenses by reducing waste, rework, and production errors.

5.3 Future Prospects

As defence technologies evolve, arc welding robots are expected to incorporate advanced features like AI-driven quality control, adaptive welding techniques, and improved mobility for field repairs. These advancements will further enhance their value in creating innovative, resilient, and efficient defence solutions. In summary, arc welding robots are indispensable in the defence sector, enabling high-quality production, efficient maintenance, and rapid innovation, all of which are crucial for national security.

6. CONCLUSION

The purpose of this research is to identify the most suitable commercial robot for arc welding. For decision-making, eight alternatives were chosen, and five criteria/attributes were considered. Using the robot's parameters, the best robot is selected using the SWI and SWEI procedures. To calculate the objective's weights of relevance to the traits and criteria, the entropy weights approach is used. According to the results, Robot-7 was the first to be chosen using both SWI and SWEI approaches. It has an average maximum reach of 4368 mm, and repeatability of 0.15 (+/-) mm with features like a payload of 6 kg, mechanical weight of 105 kg, and an average power consumption of 2.5 kW. The next alternative may be used if the first alternative is not readily accessible on the market. The SWI and SWEI techniques are more statistically straightforward and have the potential to yield more precise findings. Moreover, the robot's product line may be expanded to include additional characteristics and options. It is possible to incorporate subjective weights and identical weights when determining significant assignment weights.

The study is dedicated to the formulation, comparative analysis of two information-theoretic, probabilistic MCDM techniques, called the SWI and SWEI, within the concept of the measures of information and probability theory. Such techniques are used when particular consideration is given to the evaluation of defense systems, and there is a need to make critical decisions under circumstances of uncertainty and competing goals. The principle of the SWI method rests on the Shannon entropy and the direct weighting of information. In the SWEI method, the exponential information content transformation is used, which displays greater sensitivity to differences between alternatives. The methodology entails the fact that probability is inversely proportional to the information content, such that the alternatives that are more uncertain or information-rich have a greater impact on the decision-making process.

The case in point imparts knowledge of how information substance that runs based on criterion-level probabilities could be used to make formidable, data-driven rankings about the course of options of the defense systems. It indicates that SWEI increases discrimination among close necessities in similarly measured performances by inflating the significance of high-information character traits, which can prove helpful in instances of differences in performance that are slight. Mathematical basis is subsequently provided to every technique, extensions, as well as algorithmic procedures and normalization schemes that increase the replicability as well as generalizability in various fields.

The study can have some relevance to administrative implications in the defense decision-making wherein resource allocation, threat prioritization, as well as system selection are performed based on multi-criteria evaluations in the light of uncertainty. The methods follow up the traditional scoring methods by extending them using probabilistic MCDM tools based on the principles of information theory, where uncertainty quantification is allowed, and weighting data and extracting weighting data are done without subjective information. The suggested framework will be of use to the increasing literature in the field of entropy in decision-making, and the generalized applicability of the framework can be found in the areas of risk assessment, intelligent systems, and strategic planning.

6.1 Limitations of the Study

- Data Requirements: To effectively estimate probabilities or entropy, information measurement methods may need a large amount of data. Obtaining sufficient data for all requirements may be difficult in some circumstances
- It contains an excessive number of pairwise comparisons; it may encounter issues because of the dependency between the alternatives and the criteria
- No result may be produced if a certain value in the initial decision matrix is zero. It is this method's biggest drawback.

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