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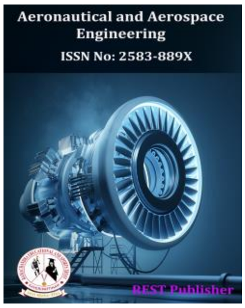

Industrial Robot Selection using TOPSIS Method: A Comparative Analysis

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Abstract. *The days when humans and robots have not yet interacted in daily activities are gone. In fact, robots are on their way to changing their applications from industry to contributing to the well-being of people in everyday life. These robots are called "social robots" (SR). Unlike robots that simply describe what helps them, social robots aim to establish social interactions and improve the socialization of human beings. While many industrial robots are primarily used by manufacturing companies for hazardous or menial tasks, social robots have become a popular choice due to their quality and the positive impact they have on productivity and profitability. Industrial robots have anthropological features and are generally reprogrammable machines. Their mechanical arms are crucial components, and they possess other, albeit less prominent, features such as decision-making abilities, a range of emotions, the ability to respond to inputs, and communication skills. They are widely used in various industries, including material handling, assembly, and machines for applications like material handling, assembly, and machines for applications. These robots play an essential role in increasing efficiency and quality. Robots in manufacturing companies are highly valued for their ability to automate tasks and be reprogrammed for different functions. They possess various features optimized for specific handling tasks, including the ability to move in two or more axes and respond to different sensory inputs. This comprehensive set of features makes them suitable for a wide range of applications, including assembly, welding, material handling, loading, packaging, and inspection, where endurance, speed, and accuracy are required. The selection of industrial robots is a decision-making process based on the needs of production. Making the right decision is crucial for productivity and success. Choosing the wrong robot can lead to issues such as inefficiency or the inability to perform specific tasks within a multi-scheduled production. In the worst-case scenario, a completely unsuitable robot can render the entire company unusable. The complexity of the selection process is amplified by the diversity of robot manufacturers, as well as the significant variations in manufacturing jobs. Manufacturers themselves have recognized the importance of addressing these challenges, particularly in relation to the demands and intensity of specific tasks. Unity of ideal solution (TOPSIS). is prioritized by, this is a multi-criteria decision Analytical method. TOPSIS Abbreviation of (PIS). Select The short geometric distance alternative is positive The best solution is, basically The Great Solution of Thought (Nis) To be negative Distance is geometric. TOPSIS The assumption is even higher is, is coming or going The benchmarks are increasing. Scaling problems or Many in the criteria Parameters Mostly Improper Dimensions Due to normalization Generally required. Alternative taken as load capacity, Maximum tip speed, Memory capacity, Manipulator reach, Repeatability, Positioning accuracy. Evaluation parameter taken as Industrial robot 1, Industrial robot 2, Industrial robot 3, Industrial robot 4, Industrial robot 5, Industrial robot 6, Industrial robot 7. From the result it is seen that Industrial robot 3 is got the first rank where as is the Industrial robot 1 is having the lowest rank. Keywords: Industrial Robot, Manufacturing industry, Tools or Facilitator teachers.*

Keywords*: Critical Temperature, Critical Pressure, Saturated pressure*

1. INTRODUCTION

Today, robots have become the primary means of entry in the manufacturing process. As new production methods emerge, robots face the challenge of meeting the requirements of flexible production systems and adapting to new job details. The development of highly flexible and programmable robots has led to advancements in artificial intelligence and automation levels within the industry. These robots possess about

100 technical parameters that can be used to describe them, as recommended by Johansson. These parameters include mechanical and control performance, installation, operation and maintenance factors, as well as cost considerations. Therefore, careful planning is required in the multifaceted process of selecting an industrial robot, with the goal of choosing a robot that best aligns with the user's intended job needs. In the present era, we are witnessing the fourth industrial revolution, characterized by cyber-physical systems, the Internet of Things (IoT), cloud computing, and human-robot interaction in smart city environments. The days when humans and robots had no contact in daily activities are long gone. In fact, robots are now on their way to changing their applications from industry to contributing to the well-being of people in everyday life. These robots, known as "Social Robots" (SR), go beyond simply assisting and are designed to establish social interactions and improve human socialization. For instance, social robots are increasingly being used in educational settings to engage with children and facilitate the educational process, serving as educational tools or assisting teachers. While many industrial robots are primarily utilized by manufacturing companies for hazardous or low-skilled tasks, choosing the right robot is of utmost importance. An incorrect selection can negatively affect productivity and profitability by compromising the quality of the products. Industrial robots possess anthropological features and are general-purpose, reprogrammable machines. The mechanical hand is a critical component, and they also exhibit other important features such as decision-making skills, the ability to respond to sensory inputs, and communication capabilities with others. Industrial robots are essential tools in various industries for applications such as material handling, assembly, finishing, machining, spray painting, and welding. When choosing a robot for industry, there are specific attributes that need to be considered. These attributes include control resolution, accuracy, repetitive load-bearing capacity, degrees of freedom, human-machine interface skills, programming flexibility, maximum speed, memory capacity, and supplier service quality. These attributes can be classified as objective or subjective, and they greatly influence the selection process. Objective attributes, such as the cost of the robot and its load capacity, can be defined numerically. On the other hand, subjective attributes, like the quality of the seller's service and programming flexibility, are more qualitative in nature. Higher values of useful attributes such as load capacity and programming flexibility are always desirable, while lower values of attributes like cost and errors are preferred. When selecting industrial robots for specific applications, decision makers need to consider all these characteristics and weigh them against the performance requirements of the robot. Industrial robot selection is a critical decision, as using and replacing unsuitable robots can significantly impact productivity and profitability. Therefore, effective selection requires the consideration of various objective and subjective attributes. These criteria can have different units and may be conflicting in nature, making it challenging for decision makers to compare and select the most suitable robot. Researchers have tackled this problem by using multiple attribute decision-making (MADM) methods, which involve normalization techniques to validate the results obtained from these methods.

2. MATERIALS & METHODS

Alternative: load capacity, Maximum tip speed, Memory capacity, Manipulator reach, Repeatability, Positioning accuracy.

Evaluation parameter: Industrial robot 1, Industrial robot 2, Industrial robot 3, Industrial robot 4, Industrial robot 5, Industrial robot 6, Industrial robot 7

Load capacity: load capacity is max is the permissible power, it's level specifications a specific when meeting at a point in the direction can be used. This fixed at maximum force (mass × gravity) and change forces (mass × acceleration) are included.

Maximum tip speed: each in the curve the point is an optimal design indicates. Current max with a tip speed of 80 m/s compared, the maximum node relaxing the speed limit reduced energy costs by up to 5.4%.

memory capacity: memory capacity is the computer, laptop, smartphone or other smart device for electronic devices like of usable memory size. Every hardware on the device or computer minimum and maximum there is memory. Of a device performance and its input /of output functions performance depends on memory capacity.

manipulator reach: robot's reach is a robot if the arm is fully extended how far can you reach? Is a measure of Total horizontal stroke the radial distance is defined as, the wrist can travel? Reach is always more than paralysis will be more. Industry arm-like structure of a robot that is the robot manipulator is called robot scheduled tasks to be performed this component is responsible for completion. Also known as robotic arm, the manipulator is in the robot body many links are loaded and has joints.

repeatability: for multiple products of the same model similar results of the capacity of the generating system repeat the measurement doable. This determination carried out by a researcher and sample products varies only in number.

positioning accuracy: positioning system accuracy conveniently in two categories separable, linear bearing with precision and bearing linear positioning accuracy. The former is routes / bearing rollers (ball and rod, cross cylinder, air bearing.

Industrial robot: industrial robot is continuously moving assembly the intensity required by the line to automate production tasks a created one. As large, heavy robots, they are an industry at standard conditions within the plant are placed, and other all labor works processes and them are coming around.

3. TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution)

TOPSIS is a method for identifying the best solution from a set of alternatives that are evaluated based on multiple criteria. It works by simultaneously reducing the distance from a nadir point and increasing the distance from the solutions in the set. The significance of TOPSIS criteria comparative weights can be combined. This paper reviews different weighing schemes and distance measurements used in TOPSIS, along with many applications and comparisons with other methods [15]. TOPSIS requires limited subjective input from decision makers, which makes it an attractive option. Only subjective input weights are needed. Thus, TOPSIS is a great alternative for reducing distance while increasing the distance to the nadir point. Although TOPSIS is widely used for many applications, it is not as widespread as attribute methods. In flexible production, variation of TOPSIS is used for selecting clippers, while in financial investment and manufacturing applications, it is used to select processes. To gain weight for TOPSIS, neural network approaches are used, and more ambiguous package extensions are implemented. Companies in specific fields use TOPSIS to compare financial ratio performance and efficiency [16]. The TOPSIS method in r value sensitivity will confirm improves weight in kind. In the formula for the value of progress has been made, i.e., the 'excessive' method. Due to the complexity of assessment problems, it is necessary to understand the relationship for better and simpler methods for the intrinsic value between alternatives [17]. In this report, a novel, modified TOPSIS method, d+ substitutes in the d−-plane, and the distance between reference points r is calculated and evaluated as a value-building process. TOPSIS has been an important branch in decision-making since its inception. Table 1 compares the characteristics of TOPSIS and AHP to clarify their features. One of the main weaknesses of TOPSIS is that it lifts weights without providing a balanced test for judgments. However, the employment of AHP is considerably restricted by the human capacity for information processing, with the ceiling being seven plus or minus two in comparison [18]. The concept of TOPSIS is that the most preferred alternative is the one that is far from the positive ideal solution but has a short distance to it, and also has a long distance to the negative ideal solution. Gelenbe also pointed out this point [19]. TOPSIS cannot directly handle this type of data, and for ranking algorithms, we adopt a TOPSIS-based approach called a-TOPSIS. In this case, there are alternatives and benchmarks [20]. In section 4, we explain our methodology with an example of the proposed algorithm. The final part concludes. The TOPSIS approach is expanded to solve non-objective linear programming problems. Jahanshaloo et al. [21] introduced the TOPSIS procedure developed by Hwang and Yoon (1981), which was adopted in this study. Hwang and Yoon (1981) recommended the use of vector normalization, which is particularly relevant for TOPSIS (Chen, 2019c). With attribute weights determined by TOPSIS, it is called e-TOPSIS, and if it is not weighted, it is called u-TOPSIS. The results can be analyzed by comparison with TOPSIS [22]. This review actually raises the issue of fairness in TOPSIS' ranking index. To answer this, a detailed analysis was conducted, which was the first objective of this study [23]. Yang and Chou also developed the TOPSIS method optimization using multiple response simulations to solve the problem with discrete factors. However, the generated design alternatives of the TOPSIS method are not likely to be applied in assessment [24]. To avoid the normalization formula used in classical TOPSIS, which increases complexity, a linear scale transformation is used to make the criteria comparable. A methodology for extending TOPSIS to the fuzzy context is proposed in this section. TOPSIS is a tool for solving decision-making problems in an ambiguous environment where a multitude of persons consider the criterion for decision-making. The data and team for decision making ambiguity in the decision-making process considering linguistic variables of all criteria weights, and depending on each criterion, estimates of each alternative are used for assessment.

4. RESULT AND DISCUSSION

TABLE 1. Industrial Robot

Industrial Robot						
	load capacity	**Maximum tip speed**	**Memory capacity**	**Manipulator reach**	**Repeatability**	**Positioning accuracy**
Industrial robot 1	60.000	2540.000	500.000	990.000	0.421	77.000
Industrial robot 2	6.350	1016.000	3000.000	1041.000	0.151	8.200
Industrial robot 3	6.800	1727.200	1500.000	1676.000	0.121	9.500
Industrial robot 4	10.000	1000.000	2000.000	965.000	0.224	14.800
Industrial robot 5	2.500	560.000	500.000	915.000	0.142	5.600
Industrial robot 6	4.500	1016.000	350.000	508.000	0.084	7.100
Industrial robot 7	3.000	1778.000	1000.000	920.000	0.124	7.400

Table 1 shows the Alternative: load capacity, Maximum tip speed, Memory capacity, Manipulator reach, Repeatability, Positioning accuracy. Evaluation parameter: Industrial robot 1, Industrial robot 2, Industrial robot 3, Industrial robot 4, Industrial robot 5, Industrial robot 6, Industrial robot 7.

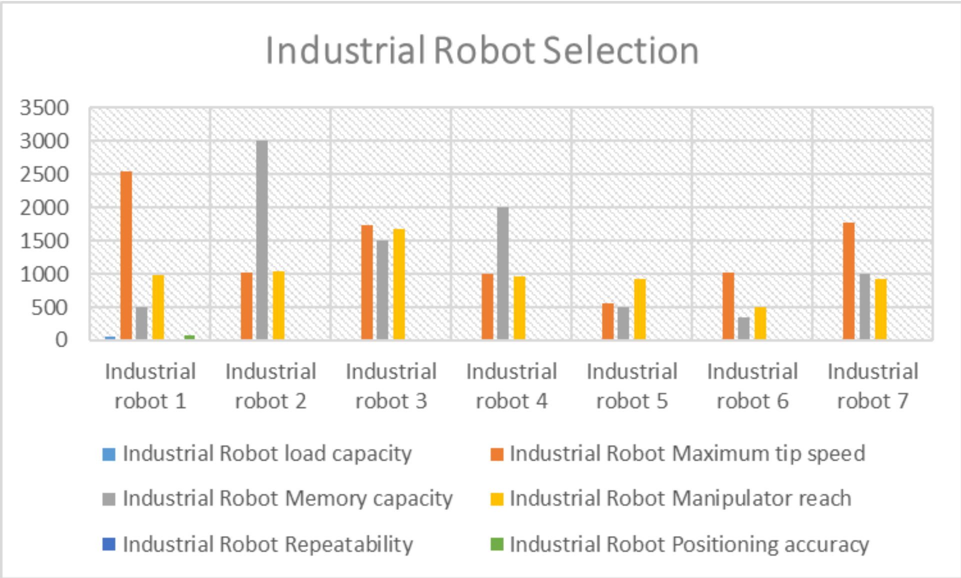

FIGURE 1. Industrial Robot

Figure 1 Shows the load capacity it is seen that Industrial robot 1 is showing the highest value for Industrial robot 5 is showing the lowest value. the Maximum tip speed it is seen that Industrial robot 1 is showing the highest value for Industrial robot 5 is showing the lowest value. the Memory capacity it is seen that Industrial robot 4 is showing the highest value for Industrial robot 6 is showing the lowest value. the Manipulator reach it is seen that Industrial robot 3 is showing the highest value for Industrial robot 6 is showing the lowest value. the Repeatability it is seen that Industrial robot 1 is showing the highest value for Industrial robot 6 is showing the lowest value. the Positioning accuracy it is seen that Industrial robot 1 is showing the highest value for Industrial robot 6 is showing the lowest value.

$$X_{n1} = \frac{x1}{\sqrt{((x1)^2 + (x2)^2 + (x3)^2 \dots)}} \quad (1).$$

TABLE 2. Squire Rote of matrix

3600.0000	250000.0000	980100.0000	0.1772	0.1772	5929.0000
40.3225	9000000.0000	1083681.0000	0.0228	0.0228	67.2400
46.2400	2250000.0000	2808976.0000	0.0146	0.0146	90.2500
100.0000	4000000.0000	931225.0000	0.0502	0.0502	219.0400
6.2500	250000.0000	837225.0000	0.0202	0.0202	31.3600
20.2500	122500.0000	258064.0000	0.0071	0.0071	50.4100
9.0000	1000000.0000	846400.0000	0.0154	0.0154	54.7600

Table 2 shows the Squire Rote of matrix value.

TABLE 3. Normalized Data

Normalized Data					
load capacity	**Maximum tip speed**	**Memory capacity**	**Manipulator reach**	**Repeatability**	**Positioning accuracy**
0.9705	0.6184	0.1797	1785.4365	0.7593	0.9594
0.1027	0.2473	1.0779	1877.4136	0.2723	0.1022
0.1100	0.4205	0.5390	3022.6178	0.2182	0.1184
0.1618	0.2435	0.7186	1740.3497	0.4040	0.1844
0.0404	0.1363	0.1797	1650.1762	0.2561	0.0698
0.0728	0.2473	0.1258	916.1634	0.1515	0.0885
0.0485	0.4329	0.3593	1659.1935	0.2236	0.0922

Table 3. Normalized Data shows the Alternative: load capacity, Maximum tip speed, Memory capacity, Manipulator reach, Repeatability, Positioning accuracy. Evaluation parameter: Industrial robot 1, Industrial robot 2, Industrial robot 3, Industrial robot 4, Industrial robot 5, Industrial robot 6, Industrial robot 7.

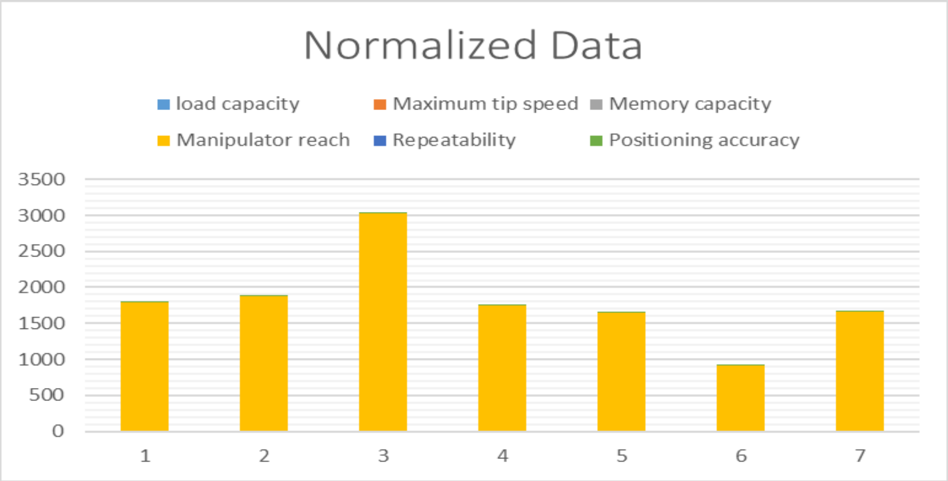

FIGURE 1. Normalized Data

TABLE 4. Weight

Weight					
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25	0.25	0.25

Table 4 Weight shows the informational set for the weight all same value 0.25.

$$X_{wnormal1} = X_{n1} \times w_1 \quad (2).$$

TABLE 5. Weighted normalized decision matrix

Weighted normalized decision matrix					
0.0038	0.1589	0.0304	0.0960	0.1898	0.2398
0.0004	0.0636	0.1826	0.1010	0.0681	0.0255
0.0004	0.1080	0.0913	0.1626	0.0546	0.0296
0.0006	0.0626	0.1217	0.0936	0.1010	0.0461
0.0002	0.0350	0.0304	0.0888	0.0640	0.0174
0.0003	0.0636	0.0213	0.0493	0.0379	0.0221
0.0002	0.1112	0.0609	0.0892	0.0559	0.0230

Table 5 Shows the Weighted normalized decision matrix values

TABLE 6. Positive Matrix

Positive Matrix					
0.0038	0.1589	0.1826	0.1626	0.0379	0.0174
0.0038	0.1589	0.1826	0.1626	0.0379	0.0174
0.0038	0.1589	0.1826	0.1626	0.0379	0.0174
0.0038	0.1589	0.1826	0.1626	0.0379	0.0174
0.0038	0.1589	0.1826	0.1626	0.0379	0.0174
0.0038	0.1589	0.1826	0.1626	0.0379	0.0174
0.0038	0.1589	0.1826	0.1626	0.0379	0.0174

Table 6 Positive Matrix shows the informational set for the value.

TABLE 7. Negetive matrix

Negative matrix					
0.0002	0.0350	0.0213	0.0888	0.1898	0.2398
0.0002	0.0350	0.0213	0.0888	0.1898	0.2398
0.0002	0.0350	0.0213	0.0888	0.1898	0.2398
0.0002	0.0350	0.0213	0.0888	0.1898	0.2398
0.0002	0.0350	0.0213	0.0888	0.1898	0.2398
0.0002	0.0350	0.0213	0.0888	0.1898	0.2398
0.0002	0.0350	0.0213	0.0888	0.1898	0.2398

Table 7 Negative matrix shows the informational set for the value

TABLE 7. SI Plus & Si Negative & Ci&Rank

	SI Plus	Si Negative	Ci	Rank
Industrial robot 1	0.3164	0.1245	0.2823	7
Industrial robot 2	0.1178	0.2962	0.7155	2
Industrial robot 3	0.1066	0.2796	0.7240	1
Industrial robot 4	0.1502	0.2373	0.6124	4
Industrial robot 5	0.2113	0.2557	0.5475	6
Industrial robot 6	0.2190	0.2699	0.5521	5
Industrial robot 7	0.1511	0.2689	0.6402	3

Table 8 shows the final result of this paper Industrial robot 3: This robot has the lowest values for both SI Plus and Si Negative, indicating a high positive sentiment and low negative sentiment associated with it. Additionally, it has the highest value for Ci, making it the most competitive among the given robots. Industrial robot 2: This robot has a relatively low SI Plus value and the second lowest Si Negative value, indicating a positive sentiment and relatively low negative sentiment. Its Ci value is the second highest, making it the second most competitive robot. Industrial robot 7: This robot has a moderately low SI Plus value and a relatively low Si Negative value. Its Ci value is the third highest, indicating a good level of competitiveness. Industrial robot 4: This robot has a higher SI Plus value compared to the previous robots, indicating a slightly lower positive sentiment. Its Si Negative value is higher as well. However, it has a relatively high Ci value, indicating decent competitiveness. Industrial robot 6: This robot has higher SI Plus and Si Negative values compared to the previous robots, indicating a lower positive sentiment and slightly higher negative sentiment. Its Ci value is also lower, suggesting lower competitiveness compared to the previous robots. Industrial robot 5: This robot has a higher SI Plus value, indicating a lower positive sentiment. Its Si Negative value is also higher, indicating a slightly higher negative sentiment. Its Ci value is the lowest among the given robots, indicating relatively lower competitiveness. Industrial robot 1: This robot has the highest SI Plus value and a relatively low Si Negative value. Its Ci value is the second lowest, indicating lower competitiveness compared to the other robots.

$$X_{si+1} = \sqrt{((X_{wn1} - X_{p1})^2 + (Y_{wn1} - Y_{p1})^2 + (Z_{wn1} - Z_{p1})^2} \quad (3)$$

$$X_{si-1} = \sqrt{((X_{wn1} - X_{n1})^2 + (Y_{wn1} - Y_{n1})^2 + (Z_{wn1} - Z_{n1})^2)} \quad (4)$$

$$X_{ci1} = \frac{X_{si-1}}{(X_{si+1}) + (X_{s(i-1)})} \quad (5)$$

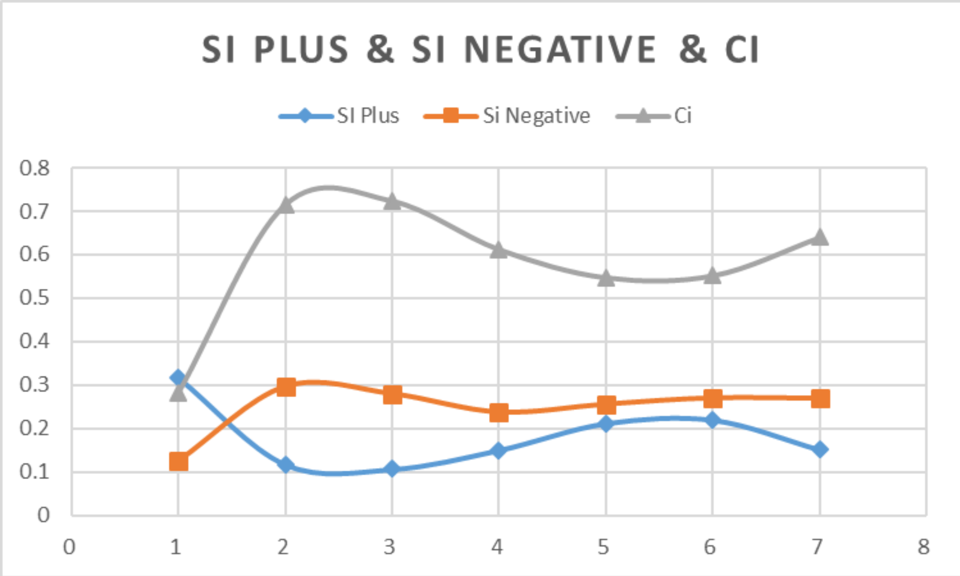

FIGURE 3. SI Plus & Si Negative & Ci

Figure 3 shows the graphical representation Si Positive & Si Negative & Ci shows the graphical representation

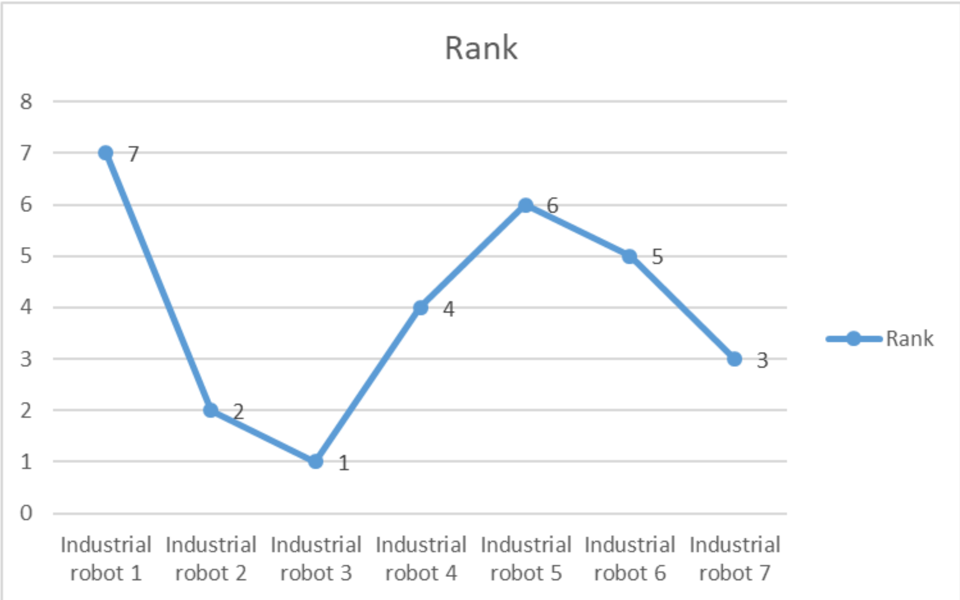

FIGURE 4. Rank

Figure 4 shows the graphical representation The Industrial robot 1 is in 7th rank, The Industrial robot 2 is in 2nd rank, The Industrial robot 3 is in 1st rank, The Industrial robot 4 is in 4th rank, The Industrial robot 5 is in 6th rank. The Industrial robot 6 is in 5th rank The Industrial robot 7 is in 3rd rank.

5. CONCLUSION

To avoid complex ambiguity in numbers, weighted estimates are used to smoothly decompose values based on the rank order mean of deletions. By calculating the distances to solutions of alternatives, both the best and negative-best, a ranking order can be determined. The coefficient defined as closeness is used to measure the proximity. A numerical example is proposed to demonstrate the calculation procedure of this method. In manufacturing companies, robot selection is always an important issue for improving product quality and increasing productivity. Robots are highly valued for their automation and reprogrammable capabilities, as well as their various features optimized for specific handling tasks. They possess the ability to move in multiple axes and respond to sensory inputs, which contributes to their comprehensive functionality. Their applications include tasks such as assembly, welding, material handling, loading, packaging, inspection, and testing, allowing for improved endurance, speed, and accuracy. In this introductory Social Robot Exam Paper, each scale is equally important in the educational environment. Therefore, the weights assigned to each criterion are the same and equal to one. However, in more specific educational scenarios, different weights may be assigned to each criterion based on the efficient implementation of educational activities according to their respective importance. the provided ranking, the order of the industrial robots from highest to lowest rank is as follows: Industrial robot 3 (1st rank), Industrial robot 2 (2nd rank), Industrial robot 7 (3rd rank), Industrial robot 4 (4th rank), Industrial robot 6 (5th rank), Industrial robot 5 (6th rank), Industrial robot 1 (7th rank)

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