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An Assessment on The Manufacturing Environment Using the Grey Relational Analysis Method

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Abstract: *Focus on sustainability growth: Sustainable practises are becoming more and more important in the manufacturing sector. Environmentally friendly programmes are being implemented by businesses to lessen their carbon footprint, cut waste production, and maximise resource use. This entails implementing recycling and waste management programmes, adopting energy-efficient industrial techniques, and investigating renewable energy sources. In order to uphold a favourable brand reputation, satisfy legal obligations, and draw in environmentally sensitive customers, sustainability has emerged as a critical component. Integration of cutting-edge technology: The adoption of cutting-edge technologies like automation, robots, artificial intelligence, and the Internet of Things (IoT) is reshaping the industrial industry. The industrial processes are being revolutionised by these technologies, which are also enhancing operational effectiveness and enabling real-time data monitoring and analysis. Robotics and automation are accelerating the productivity of routine tasks. Economic Impact: Manufacturing is important to the growth of the GDP, employment, and technological advancements in the world economy. Research in this area assists in identifying variables that can boost manufacturing processes' productivity and efficiency, resulting in increased economic growth and global competitiveness. It also helps to comprehend how manufacturing affects the growth of the labour force, income inequality, and local economies. Sustainable Development: The environment, resource consumption, and waste generation are all significantly impacted by manufacturing activity. An understanding of how to reduce the environmental impact of manufacturing processes, increase resource efficiency, reduce waste production, and encourage the use of cleaner technology can be gained from research on sustainable manufacturing practices. Lean manufacturing is a practise that concentrates on cutting waste and increasing productivity in manufacturing operations. It makes use of methods including just-in-time production, value stream mapping, standardised work, and continuous improvement. To find waste, restructure processes, and maximise resource use, researchers use lean manufacturing approaches. In the manufacturing sector, this practise aids in increasing productivity, cutting costs, and raising overall operational performance. The process of simulation modelling entails developing computer-based models that closely resemble actual production systems. By analysing multiple situations, putting different parameters to the test, and gauging the effects of adjustments to system operation or design, researchers utilise simulation modelling to examine and improve manufacturing processes.***"***ASEA-IRB60/2,CincinnatiMilacroneT3-726,CybotechV15ElectricRobot, HitachiAmericaProcessRobot,UnimationPUMA500/600,UnitedStatesRobotsMaker110,YaskawaElectric MotomanL3C".***"***Load capacity (LC)(kg), Repeatability (RE)(mm), Maximumtipspeed (MTS)(mm/s), Memorycapacity(MC), Manipulatorreach(MR)(mm)"* cybotechv15electricrobot has secured the 1st rank i when compared to other robots.*soil texture performed well in land evaluation techniques when copared to others***.**

Keywords: *Manipulator reach, ROBOTS, Memory capacity, Electric Robot.*

1. INTRODUCTION

Manufacturing resource planning's main goal is to ensure that the ideal amount of a product is produced and supplied at the appropriate time while minimising costs and taking system restrictions like resource availability into account. Planning is frequently carried out in manufacturing environments utilising the material requirements planning (MRP) logic, although MRP has severe limitations when it comes to addressing uncertainty. In contemporary manufacturing businesses, production planning operations are tightly regulated "by the usage of MRP, Manufacturing Resource Planning II (MRP II), Enterprise Resource Planning (ERP), and ERP II. For integrated production data, such as demand, supply, product information, inventory, accounting, costing, lead-time, and routing, these systems act" as central repositories. They continue to have difficulty handling and responding to uncertainty, though, which causes expected order release timelines to vary from those produced by an MRP system. Additionally, capacity restrictions are not taken into account by MRP logic. Planners usually have to make regular adjustments to their plans in order to account for these fundamental problems because of the inherent limits of MRP planning techniques [1].Not just among major industrial enterprises like General Electric, Westinghouse, and General Motors, but also among numerous smaller businesses, there has been an increase in the need for better performance from suppliers of raw materials and acquired parts. These businesses rely on vendors to provide them with modest numbers of high-quality items on schedule; otherwise, they risk losing important contracts. The foundations of Japanese manufacturing philosophy can be traced back to this emphasis on vendor performance. In order to maintain low manufacturing costs and excellent product quality, it is widely understood that vendor performance is vital. As they ensure the prompt delivery of components and materials for the manufacturing process, materials managers have a crucial role in managing vendor performance. Finding problems with vendor performance as businesses adopt the just-in-time manufacturing philosophy becomes even more important. Companies can increase their productivity in purchasing decisions, production scheduling, and inventory control by properly addressing issues brought on by subpar vendor performance [2].The process of "decision-making entails the process of locating and choosing alternatives in accordance with the decision-maker's values and preferences". When presented with a decision, it is crucial to not only recognise as many different possibilities as you can, but also pick the one that best fits your goals, ambitions, aspirations, and beliefs. Every decision-making procedure ends with a final decision. Both business and daily life require the ability to solve problems and make decisions. Making decisions is frequently necessary for problem solving, and it is crucial in management and leadership jobs. Even if some people may have a natural propensity for making judgements, it is crucial for them to concentrate on raising the calibre of their choices. On the other hand, people who may not be inherently good at making decisions can still assess circumstances well, but they should focus on being more decisive in acting on their evaluations [3].Large industrial plants can provide a number of difficult implementation issues. Large organisations frequently struggle with how to distribute resources across many projects. It can be challenging to decide where to start implementing process improvement projects since there are so many different manufacturing processes and various functions involved, each with its own set of products. On the starting point, several team members might have contrasting views, each with their own reasoning. A approach that can identify areas with the greatest potential for improvement and prioritise and select improvement initiatives in accordance with that information is required to address this issue. This methodology should also take into account things like process variables, resource limitations, and operator capabilities. "The main contribution of this research is the creation of a novel method" that, while prioritising improvement initiatives, also finds the best problem-solving techniques to apply in each situation. Large manufacturing facilities can improve their decision-making process by using this methodology to efficiently identify the areas with the most promising improvement prospects, prioritise projects, and allocate resources in line with those priorities. In the manufacturing setting, this strategy tries to maximise the overall efficiency and effectiveness of process improvement projects [4].Over the past 20 years, manufacturing companies have adopted a variety of practises to improve their operations in response to fierce competition. "Quality circles, statistical process control, theory of constraints, just-in-time inventory management (JIT), total quality management (TQM), six sigma, and total preventative maintenance (TPM) are a few examples of these practices". These procedures are now understood to be essential parts of "a lean manufacturing strategy, which attempts to establish a cohesive and cogent system that consistently provides consumers" with improved value. Integration of all business operations and processes into a single, cohesive system is a crucial component of the lean manufacturing approach. Aligning accounting and control systems with the entire plan is necessary for this integration. The integration of management accounting and control practises, however, lacks empirical support. Within a lean manufacturing strategy[5].

Spectrometric data is used in the production of plastics to measure and express colour using three or four variables. The three primary colours and intensity are commonly represented by these factors. To ensure good colour blending and to spot any inconsistencies, such as an abundance or deficiency of a particular pigment, this data can be properly monitored. Similar to this, final parts are checked for dimensional conformity using coordinate measurement equipment during the production of aircraft engines. The goal is to identify the precise sets of dimensions and subsequent machining processes that led to the creation of a nonconforming item. It's vital to note that the variables being monitored in these applications may include both various processing factors (such as machine speed, temperature settings, and pressure settings) as well as quality characteristics of the components themselves (such as colour, strength, and elasticity). Although the example is set in a manufacturing environment, the proposed approach is not restricted to just those kinds of settings. It can be used in a variety of situations where monitoring variables are important for maintaining quality and locating areas that need improvement [6].Large businesses have historically used “Manufacturing Resource Planning (MRPII) and Material Requirements Planning (MRP) systems for production planning and scheduling”. But from these systems, a new one known as Enterprise Resource Planning (ERP) has arisen over the past ten years. Nowadays, ERP systems are viewed as integrated information systems that cover the entire company. ERP systems are designed to facilitate the seamless interchange of information between numerous departments within an organisation, including those responsible for “finance, accounting, sales, marketing, planning, production, purchasing, human resources, logistics, and distribution”. Their goal is to manage the complete organisational process in a disciplined and organised manner, assisted by the system, commencing with the receipt of a customer order and continuing through manufacturing and ultimate delivery [7].The top five manufacturers of ERP systems are Oracle, BaaN, JDEdwards, and PeopleSoft. The ERP market was expected to reach a value of “USD 69 billion by 2003, with an estimated compound annual growth rate of 32%, according to a prediction made by Boston-based Advanced Manufacturing Research (Angerosa, 1999)”.The adoption of “a suitable MRP, MRPII, or ERP system has become essential for the survival of many manufacturing firms” as customer expectations continue to change and include requests “for shorter delivery lead times, more agility, improved quality, and lower prices”. These technologies are crucial for achieving consumer expectations and maintaining manufacturing organisations' competitiveness in the fast-paced business world of today [8].An method to cost management known as functional cost analysis centres on the functions that a product performs. Functional cost analysis evaluates a product's primary functions from the standpoint of its service potential to customers rather than concentrating on the physical elements and components. For instance, the primary purpose of a pen is "to make a mark," whereas the primary purpose of a staple remover is "to remove a staple."This strategy takes a more abstract perspective of the product by adopting a functional perspective. Thinking in terms of functions rather than parts has the benefit of allowing for a more creative and revolutionary product redesign. Beginning with the already-existing components, the final product is frequently a somewhat changed version of the original [9].Material Requirements Planning (MRP), a successful strategy in manufacturing since the 1970s, has gained widespread acceptance. Its main objective is to identify the parts and components required to meet product requirements. Key issues including what needs to be produced, what is required for production, what inventory is present, and what is lacking are addressed by MRP. These questions can be resolved using MRP, which provides efficient material planning and control. The primary purpose of MRP is to convert the Master Production Schedule (MPS) into a thorough breakdown of the necessary materials and the accompanying production orders. It also helps to specify the importance of these requests and the production capacity needed. This method was first created in the 1970s, and not much has changed since then. It is important to keep in mind that MRP was created to fit the industrial environment of the time and might not entirely correspond with the demands and complexity of contemporary manufacturing practises. The limits of MRP have become increasingly obvious as manufacturing procedures have developed over time. Therefore, in order to meet the needs and problems of modern industrial firms, newer and more sophisticated planning methods are required [10].

A revolutionary method called e-Manufacturing uses wireless and web-enabled technology to create manufacturing operations with predictive, almost zero-downtime performance. E-Manufacturing provides the seamless integration of data flow at the machine/process level, information flow at the factory and supply system level, and cash flow at the business system level by utilizingemotronicstechnology. The primary objective of e-Manufacturing is to fully integrate all business components, including suppliers, networks for customer support, manufacturing companies, and assets on the shop floor. Web-enabled, tether-free, and cognitive computing technologies all help to make this integration easier. These technologies fulfil the needs of e-business and e-commerce practices while enabling connectivity and real-time intelligence. “Supply chain management (SCM), enterprise resource planning (ERP), and customer relationship management (CRM) are a few examples of closely coupled technologies that fall under the umbrella of e-Manufacturing”. Additionally, it takes into account labour and environmental laws and regulations, assuring compliance and long-term production methods. Monitoring plant floor assets, predicting fluctuations in product quality, and foreseeing equipment performance losses are some of the essential characteristics of e-Manufacturing. This makes it possible to dynamically reschedule production and maintenance tasks, improving overall effectiveness and productivity [11]. In order to cut down on manufacturing lead times and boost throughput, a plant's overall productivity and efficiency must have a well-designed facility architecture. Manufacturing systems frequently employ the following layout configurations: process layout, flowline or single line layout, multi-line layout, semi-circular layout, and loop layout. The physical organization and traffic flow of the facility's machinery and workstations are determined by these layouts. Based on the commonality of their functions or processes, machines and workstations are placed together in a process layout. As a result, the facility can be flexible and accommodate many different goods or processes. Machines and workstations are placed in a linear production line-like fashion in a flowline or single line architecture. This design is suitable for high-volume production with a standardized process flow [12]. Organizations strive for nearly flawless quality in the current highly competitive global market because of the slim profit margins brought on by the rivalry. The importance of quality is made even more clear by the fact that a warranty incident or a bad customer experience may significantly affect a company's profits and reputation. Customers may now share their experiences and opinions thanks to the Internet and social media platforms, making it vital for businesses to uphold high standards and handle any concerns as soon as they arise. Mature organizations have incorporated several quality-oriented ideologies like business excellence, lean manufacturing, standards conformance, six sigma, and design for six sigma in order to attain exceptional quality. By utilizing these strategies, businesses hope to reduce flaws and guarantee that their manufacturing processes yield only a few defects per million opportunities [13].

2. MATERIALS & METHODS

***ASEA-IRB60/2*:** Versatility: The ASEA-IRB60 is incredibly “adaptable and capable of carrying out a variety of activities”. It can perform complex operations and adapt to various manufacturing needs because of its multi-axis movement capabilities and configurable functionality. This robotic device is renowned for its accuracy and quickness. To guarantee precise positioning and reliable performance, it makes use of cutting-edge sensors and control algorithms. The ASEA-IRB60's high-speed capabilities enable it to do jobs quickly and effectively, boosting output and decreasing cycle times in industrial environments.

CincinnatiMilacroneT3-726: An extremely sophisticated machine tool that provides great precision and efficiency in production processes is the Cincinnati Milacron T3-726.The Cincinnati Milacron T3-726 establishes a new benchmark in the industry with its cutting-edge features and technology, allowing producers to produce better products with higher output.

CybotechV15ElectricRobot: A cutting-edge robotic system that runs on electricity, the Cybotech V15 Electric Robot offers a quick and effective solution for many industrial applications. The Cybotech V15 Electric Robot is the perfect choice for jobs like assembling, welding, and material handling in manufacturing environments thanks to its sophisticated capabilities and adaptable design, which increase productivity, improve precision, and improve safety**.**

Hitachi America Process Robot: A cutting-edge robotic system that runs on electricity, the Cybotech V15 Electric Robot offers a quick and effective solution for many industrial applications. The Cybotech V15 Electric Robot is the perfect choice for jobs like assembling, welding, and material handling in manufacturing environments thanks to its sophisticated capabilities and adaptable design, which increase productivity, improve precision, and improve safety**.**

UnimationPUMA500/600: A well-known robotic system created by Unimation, the PUMA 500/600 is renowned for its adaptability and accuracy in industrial applications. The Unimation PUMA 500/600 delivers remarkable dexterity and agility thanks to its sturdy design and sophisticated control algorithms, making it appropriate for jobs like assembly, material handling, and welding in a variety of industries like automotive, aerospace, and electronics.

YaskawaElectricMotomanL3C: A renowned global manufacturer of industrial robots, Yaskawa is the maker of the Yaskawa Electric Motoman L3C. It is suited for a variety of applications due to its high-speed and high-precision capabilities. The Yaskawa Electric Motoman L3C has a small footprint and adaptable capabilities that make it simple to integrate into different manufacturing lines. It improves productivity, efficiency, and quality in sectors like automotive production, electronics assembly, and material handling thanks to its sophisticated control system and intelligent programming.

Load capacity (LC)(kg): Load capacity (LC) refers to the maximum weight that a particular structure, equipment, or device can safely support or handle. It is typically measured in kilograms (kg) and is an important consideration in various industries such as construction, logistics, and manufacturing. The load capacity (LC) specification is crucial for determining the suitability of equipment for a specific task. It ensures that the equipment can safely bear the intended load without risking damage, failure, or compromising safety. It is essential to adhere to the recommended load capacity guidelines to prevent accidents, maintain operational efficiency, and prolong the lifespan of the equipment.

Repeatability (RE)(mm): The ability of a robotic system or machine to repeatedly and correctly return to a particular position or point within a given tolerance is known as repeatability (RE). It is a crucial performance characteristic in precision applications and is normally measured in millimetres (mm). The level of precision and dependability that may be expected from a robotic system or machine is indicated by the repeatability (RE) parameter. A lower repeatability number denotes positioning accuracy and consistency at a higher degree. In applications requiring accurate positioning and repetitive tasks, such as assembly, pick-and-place operations, and quality inspection, this characteristic is essential.

Maximumtipspeed (MTS)(mm/s): Maximum tip speed (MTS) is the maximum linear speed that a machine's tool or tip may travel at. It is a significant performance parameter in a variety of applications, including cutting,

machining, and material processing, and is commonly measured in millimetres per second (mm/s). The highest speed that a tool or machine tip may travel is indicated by the maximum tip speed (MTS) specification. It is essential for figuring out the effectiveness and productivity of procedures that call for quick movements. In applications like CNC machining, laser cutting, and robotic milling, a higher maximum tip speed enables quicker material removal or processing, lowering cycle times and enhancing total throughput.
Memory capacity (MC): The term "memory capacity" (MC) describes how much data or information may be stored in a specific device or system. Depending on the size of the storage, it is often expressed in quantities like bytes, kilobytes, megabytes, or gigabytes. Computers, smartphones, and digital cameras are just a few examples of the many electronic gadgets where the memory capacity (MC) specification is a crucial factor. It establishes the volume of information that can be saved, including computer programmes, files, documents, pictures, videos, and other types of digital content. More data may be stored in a smaller amount of memory space, giving users more storage options and flexibility.
Manipulator reach (MR)(mm)**:** The maximum length or distance that a robotic manipulator arm can extend or reach is referred to as manipulator reach (MR). It is a crucial specification in establishing the workspace and flexibility of a robotic system and is commonly measured in millimetres (mm).In many applications, including pick-and-place operations, assembly, and material handling, the manipulator reach (MR) specification is essential. A robotic arm with a longer reach can access a larger working area, move objects in various postures, and reach into tight areas. It increases the adaptability and effectiveness of the robotic system by allowing flexibility in performing tasks within the designated reach range.

3. GRA METHOD

Grey Relational Analysis, or GRA, is a methodology applied throughout the decision-making and optimisation processes. When dealing with several criteria or factors that need to be assessed and rated, it is very helpful. An outline of the GRA technique is given below: Describe the issue: Establish the criteria or factors that must be taken into account and state the issue or choice that has to be addressed clearly. Data normalisation Transform each criterion's raw data into dimensionless or normalised values. By doing this, any scale or unit discrepancies between the requirements are removed. Identify the reference order: The ideal or desirable values for each criterion should be represented by a reference sequence. This sequence acts as a standard for contrast. Calculate the grey connection coefficient between each alternative or option and the reference sequence for each criterion. The strength of correlation between two sequences is determined by the grey relational coefficient, which also quantifies how similar two sequences are to one another. Do the grey relationship grade calculation: “To determine a grey relational grade, add the grey relational coefficients for each alternative across all criteria”. The total performance or ranking of each choice is shown by this grade. Choose the best alternative: Choose the option with the highest rating among the alternatives based on a comparison of their grey relational grades. Sensitivity assessment Conduct a sensitivity analysis to evaluate the results' stability and dependability. Testing the effects of slight changes in the weights of the criterion or the reference order on the resultant ranking is involved in this. The GRA technique offers decision-makers a systematic way to assess and rank options based on many criteria. By taking into account the relative correlations and connections between the choices and the reference sequence, it aids in determining the best answer. When presented with complicated decision scenarios containing several factors and criteria, this strategy enables decision-makers to make better informed decisions.

4. RESULTS AND DISCUSSION

TABLE 1. Performance of industrial robots

Robot	**Maximumtipspeed (MTS)(mm/s)**	**Memory capacity (MC)**	**Manipulator reach (MR)(mm)**	**Load capacity (LC)(kg)**	**Repeatability (RE)(mm)**
ASEA-IRB60/2	2540	500	990	60	0.4
CincinnatiMilacroneT3-726	1016	3000	1041	6.35	0.15
CybotechV15ElectricRobot	1727.2	1500	1676	6.8	0.1
HitachiAmericaProcessRobot	1000	2000	965	10	0.2
UnimationPUMA500/600	560	500	915	2.5	0.1
UnitedStatesRobotsMaker110	1016	350	508	4.5	0.08
YaskawaElectricMotomanL3C	177	1000	920	3	0.1

Table 1 presents a summary of performance attributes for various industrial robots, including their maximum tip speed, memory capacity, manipulator reach, load capacity, and repeatability. The ASEA-IRB60/2 robot, for example, is characterized by a maximum tip speed of 2540 mm/s, a memory capacity of 500, a manipulator reach of 990 mm, a load capacity of 60 kg, and a repeatability of 0.4 mm. Similarly, the Cincinnati Milacrone

T3-726 robot has a maximum tip speed of 1016 mm/s, a memory capacity of 3000, a manipulator reach of 1041 mm, a load capacity of 6.35 kg, and a repeatability of 0.15 mm. The other robots listed, such as the CybotechV15ElectricRobot, Hitachi America Process Robot, Unimation PUMA 500/600, United States Robots Maker110, and Yaskawa Electric Motoman L3C, also possess distinctive specifications in terms of their performance capabilities. These details provide valuable insights into the robots' speed, memory, reach, strength, and precision, which are crucial factors to consider when selecting the most suitable industrial robot for specific applications.

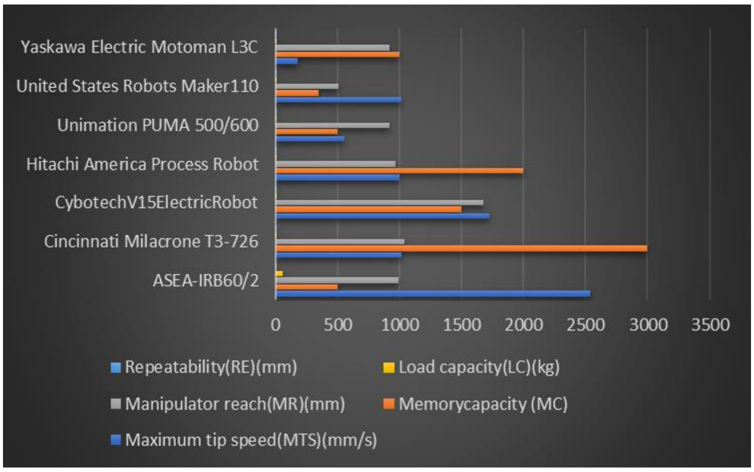

FIGURE 1. Performance of industrial robots

Figure 1 shows the performance characteristics of various industrial robots, including parameters such as maximum tip speed, memory capacity, manipulator reach, load capacity, and repeatability. For example, the ASEA-IRB60/2 robot has a maximum tip speed of 2540 mm/s, a memory capacity of 500, a manipulator reach of 990 mm, a load capacity of 60 kg, and a repeatability of 0.4 mm. Likewise, the Cincinnati Milacrone T3-726 robot exhibits a maximum tip speed of 1016 mm/s, a memory capacity of 3000, a manipulator reach of 1041 mm, a load capacity of 6.35 kg, and a repeatability of 0.15 mm. The other listed robots, such as the CybotechV15ElectricRobot, Hitachi America Process Robot, Unimation PUMA 500/600, United States Robots Maker110, and Yaskawa Electric Motoman L3C, each possess their own unique specifications in terms of performance capabilities. These details provide valuable insights into essential factors like speed, memory, reach, strength, and precision, aiding in the selection of the most suitable industrial robot for specific applications.

TABLE 2. Normalized Data

1.0000	0.0566	0.4127	0.0000	0.0000
0.3551	1.0000	0.4563	0.9330	0.7813
0.6560	0.4340	1.0000	0.9252	0.9375
0.3483	0.6226	0.3913	0.8696	0.6250
0.1621	0.0566	0.3485	1.0000	0.9375
0.3551	0.0000	0.0000	0.9652	1.0000
0.0000	0.2453	0.3527	0.9913	0.9375

Table 2 displays the results of the Grey Relational Analysis (GRA) method, which provides normalized data for the performance attributes of different industrial robots. The normalized values indicate the relative importance or ranking of each attribute for each robot. This normalization process enables easier comparison and evaluation of the robots' relative performance based on these attributes. Overall, the GRA method facilitates a more streamlined assessment of the robots' performance characteristics.

TABLE 3. Deviation sequence

0.0000	0.9434	0.5873	1.0000	1.0000
0.6449	0.0000	0.5437	0.0670	0.2188
0.3440	0.5660	0.0000	0.0748	0.0625
0.6517	0.3774	0.6087	0.1304	0.3750
0.8379	0.9434	0.6515	0.0000	0.0625
0.6449	1.0000	1.0000	0.0348	0.0000
1.0000	0.7547	0.6473	0.0087	0.0625

Table 3 presents the outcome of the GRA (Grey Relational Analysis) method, showcasing a deviation sequence for different performance attributes of industrial robots. This sequence illustrates the relative deviation or disparity between each robot's attribute value and the best attribute value observed among all the robots. By examining the deviation values, it becomes possible to determine the robots that exhibit the smallest or largest deviations from the best-performing robot in each attribute category. This analysis provides valuable insights into the relative performance and characteristics of the robots based on attributes like maximum tip speed, memory capacity, manipulator reach, load capacity, and repeatability.

TABLE 4. Grey relation coefficient

1.0000	0.3464	0.4598	0.3333	0.3333
0.4367	1.0000	0.4791	0.8819	0.6957
0.5924	0.4690	1.0000	0.8699	0.8889
0.4341	0.5699	0.4510	0.7931	0.5714
0.3737	0.3464	0.4342	1.0000	0.8889
0.4367	0.3333	0.3333	0.9350	1.0000
0.3333	0.3985	0.4358	0.9829	0.8889

Table 4 displays the Grey Relation Coefficient values, which indicate the correlation or similarity between the attribute values of various industrial robots and the reference values. A coefficient of 1.0000 signifies a perfect correlation, while lower values indicate a weaker correlation. For instance, the ASEA-IRB60/2 robot has a coefficient of 1.0000 for maximum tip speed (MTS), indicating a strong correlation with the reference value. Conversely, the Cincinnati Milacrone T3-726 robot has a coefficient of 0.4367 for maximum tip speed, suggesting a relatively weaker correlation. The coefficients for memory capacity (MC), manipulator reach (MR), load capacity (LC), and repeatability (RE) are also provided for each robot, enabling comparisons of correlation levels between their attribute values and the reference values. By examining Table 4, one can assess the level of similarity between the robots' performance attributes and the reference values, offering insights into their relative performance and characteristics.

TABLE 5. Gray Relation grade and Rank

Industrial Robot	GRG	Rank
ASEA-IRB60/2	0.4946	7
Cincinnati Milacrone T3-726	0.6987	2
CybotechV15ElectricRobot	0.7640	1
Hitachi America Process Robot	0.5639	6
Unimation PUMA 500/600	0.6086	3
United States Robots Maker110	0.6077	5
Yaskawa Electric Motoman L3C	0.6079	4

Table 5 displays the Gray Relation Grade (GRG) and Rank for various industrial robots. The GRG represents the overall performance evaluation of each robot based on its attribute values and their correlation with the reference values. Higher GRG values indicate better overall performance. Among the listed robots, the CybotechV15ElectricRobot achieved the highest GRG score of 0.7640, indicating superior overall performance. The Cincinnati Milacrone T3-726 robot obtained a GRG value of 0.6987, securing the second position. The remaining robots, including the Yaskawa Electric Motoman L3C, Unimation PUMA 500/600, United States Robots Maker110, Hitachi America Process Robot, and ASEA-IRB60/2, have GRG values of 0.6079, 0.6086, 0.6077, 0.5639, and 0.4946, respectively, reflecting their relative performance compared to the reference values. The robots are ranked in descending order based on their performance evaluation. The CybotechV15ElectricRobot holds the top rank of 1, indicating the best overall performance among the listed robots. The Cincinnati Milacrone T3-726 robot is ranked second, followed by the Unimation PUMA 500/600, United States Robots Maker110, Yaskawa Electric Motoman L3C, Hitachi America Process Robot, and ASEA-IRB60/2, with ranks 3, 4, 5, 6, and 7, respectively. The rank column provides a clear understanding of the relative standings of the robots based on their performance evaluations using the GRG values.

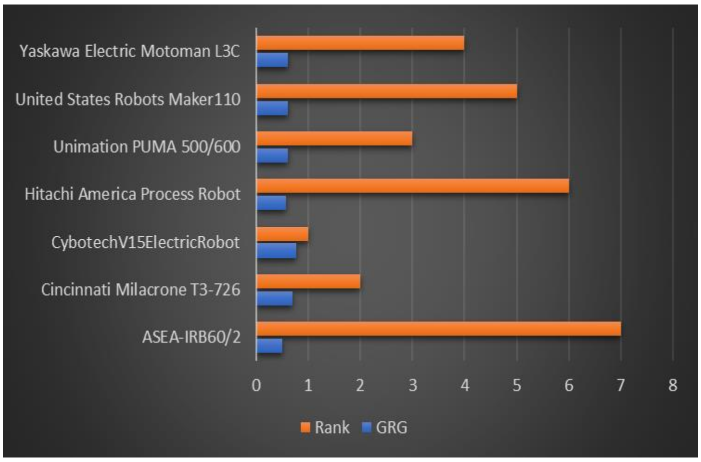

FIGURE2. Gray Relation grade and Rank

Figure 2 illustrates the ranking of industrial robots based on their Gray Relation Grade (GRG) for performance evaluation. The robots are arranged in descending order from the highest rank to the lowest. The CybotechV15ElectricRobot achieved the top rank of 1, indicating its superior overall performance compared to the other listed robots. Following closely, the Cincinnati Milacron T3-726 robot obtained the second rank. Subsequently, the Animation PUMA 500/600, United States Robots Maker110, Yaskawa Electric Motorman L3C, Hitachi America Process Robot, and ASEA-IRB60/2 secured ranks 3, 4, 5, 6, and 7 respectively. The rank column provides a clear and concise representation of the robots' relative standings based on their performance evaluations using the GRG values.

5. CONCLUSION

In conclusion, the demands of a fiercely competitive global market have resulted in substantial shifts and alterations in the production environment. Due to the fierce competition and small profit margins facing businesses today, efficiency, productivity, quality, and customer satisfaction must be prioritized enhance their operations and achieve a competitive advantage, manufacturing businesses are implementing cutting-edge approaches and technology. To improve overall quality and lower errors, integrated approaches based on quality-oriented concepts like lean manufacturing, Six Sigma, and others have emerged. The way organizations detect and handle quality concerns has been revolutionized by the use of data-driven insights, machine learning algorithms, and optimization techniques.The relevance of connectivity and integration is also increasing in the production environment. To effectively satisfy client demands, they must put agility, innovation, and reactivity first. Additionally, it is becoming more crucial than ever to keep a sharp focus on sustainability, legal compliance, and environmental awareness. A variety of abilities are required for effective decision-making, including the ability to generate and recognize choices creatively, good judgement, decisiveness, and successful decision implementation. Because of technological improvements, rising customer expectations, and the need for continual improvement, the production environment is changing quickly. Manufacturing organizations will be better prepared for success in the cutthroat global market if they embrace these changes, put effective quality management systems in place, and put customer satisfaction first.

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