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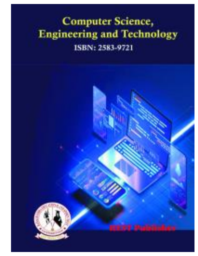

"Harnessing the Power of Artificial Intelligence in Flexible Manufacturing Systems: Enhancing Efficiency, Adaptability, and Competitiveness"

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Abstract: *A promising paradigm in contemporary manufacturing is the fusion of Artificial Intelligence (AI) technology with Flexible Manufacturing Systems (FMS). FMS, characterized by their ability to adapt to dynamic production demands, have found a perfect ally in AI, which offers advanced capabilities in data analysis, decision-making, and process optimization. This abstract provides an overview of the synergistic relationship between AI and FMS and highlights the potential benefits and challenges associated with their integration. Firstly, this abstract explores the role of AI in FMS, focusing on three key areas: planning and scheduling, intelligent control, and predictive maintenance. FMS is equipped with AI technologies like machine learning and deep learning to quickly analyze massive amounts of data, spot trends, and make precise predictions. These capabilities enhance production planning by optimizing resource allocation, reducing setup time, and minimizing production downtime. Additionally, intelligent control systems powered by AI enable real-time adjustments in response to changing conditions, leading to improved system flexibility, agility, and responsiveness. Due to a number of strong arguments, the combination of Flexible Manufacturing Systems (FMS) with Artificial Intelligence (AI) is of great research significance. The research significance of combining AI with Flexible Manufacturing Systems lies in the potential to significantly enhance operational efficiency, adaptability, and decision-making capabilities in manufacturing. This integration enables manufacturers to optimize resource utilization, mitigate downtime, and proactively manage maintenance, ultimately leading to improved productivity, cost savings, and competitiveness. By addressing the challenges and exploring the opportunities offered by AI in FMS, researchers can contribute to the advancement and transformation of the manufacturing industry. Due to the abundance of possibilities offered on the global market, conflicting situations can develop while choosing a certain motorcycle. There may be many alternatives to the initial choice or there may not always be a fixed amount of possibilities available. The possibility of not having an acceptable option for the criterion exists as well. "Multiple Criteria Decision Making" is a technique designed for the optimization of problems with an "infinite or finite number of choices" and the MCDM technique. "WSM method" is used to optimize the process in this paper.*
In artificial intelligence with flexible manufacturing system evaluated six criteria and got the values. in that values .FMS 1 has got the first rank, FMS 2 got the second rank,FMS 3 got the third rank and FMS 4 got the last rank.In conclusion, the integration of AI with Flexible Manufacturing Systems offers numerous opportunities for enhanced operational efficiency, productivity, and adaptability.
Keywords: *Artificial Intelligence, FMS, Adaptability, Expandability, Quality of results and MCMD.*

1. INTRODUCTION

In the area of artificial intelligence, the vast majority of crowd sourcing projects are automated services. Machine learning crowd sourcing comprises making products and services available for widespread use. For machines executing NLP and NLU tasks including classification, feature engineering, decision-support systems, and text categorization, data labelling is advantageous [1]. A potential approach for creating and encouraging more robust supply networks is artificial intelligence (AI). The literature on the use of AI to supply-chain management is, however, a little disjointed. The development of research and practise on an exciting interface for discovering and putting into practise effective AI techniques to increase supply-chain resilience (SCRes) is hampered by the dearth of a decision-making framework in the literature to date. In this paper, we propose an integrated Multi-criteria decision making (MCDM) technique that is powered by AI-based algorithms like Fuzzy systems, Wavelet Neural Networks (WNN), and Evaluation based on Distance from Average Solution (EDAS) in order to find patterns in AI techniques for developing various SCRes strategies.[2] AI is based on a number of tools, techniques, and formulas. It is used to enable systems (machines or pieces of equipment) to learn from information and data collected from their surroundings and to manage the resulting cognitive utilities to support people's ability to complete challenging activities [2]. Technology that uses artificial intelligence (AI) to enable auditing not only makes accurate and thorough audits possible for CPA companies, but it also represents a significant advancement in the current context of auditing. Applications of an artificial intelligence-enabled auditing technique in external auditing can improve auditing effectiveness, raise financial reporting accountability, guarantee audit quality, and help decision-makers make sound choices.[7]. HFA has been studied from a variety of angles, including engineering, psychology, physiology, and ergonomics. To increase system safety from a human standpoint, many standard strategies have been created and put to use. However, the use of artificial intelligence-driven systems, industry 4.0, and emerging socio technical systems exposes these approaches' weaknesses. This necessitates the development of smart tactics that incorporate both human and artificial intelligence (AI) components. This study examined how expert systems and artificial intelligence were integrated into HFA [12]. Using artificial intelligence approaches, modeling human characteristics and forecasting human performance have become two of the most important topics of study in recent years. Researchers feed various artificial intelligence techniques with historical, observational, and simulation data as well as knowledge from subject matter experts. One of the divisions of artificial intelligence is deep learning.[12] Artificial intelligence has a firm handle on the ways that market perceptions are currently spreading. Currently, artificial intelligence is practically being used across a number of industries.. Financial institutions are utilizing artificial intelligence in highly sophisticated ways. The financial sector is experiencing a fantastic tidal wave thanks to the amazing creation of artificial intelligence is being used to reduce time consumptions, cut costs, and moreover bring in added value with faster assistance in the majority of daily parts of the financial business (Eletter, Yaseen, & Elrefae, 2010). It is also asserted that the well-known, top-tier, international corporate financial sectors rely on artificial intelligence, which has been put in place to take advantage of technological advancements and provides customers with superior functional assistance, illumination of performance, and increased revenue sources (To & Lee, 2010).[13]

2. FMS (Flexible Manufacturing System)

"Flexible manufacturing system" (FMS) is the name given to a set up of components connected by a transport system. The transporter delivers work to the machines on pallets or other interface units in order to offer precise, speedy, and automatic work-machine registration. A central computer controls the operation of the equipment and the transportation network. Alternatively, "FMS consists of a collection of processing workstations connected by automated material handling and storage system and managed by integrated computer control system." Due to the fact that it can process multiple different part styles at once at the workstation and that it may change production volumes in response to changing demand patterns., FMS is known as flexible.[21] Industries are able to produce a variety of products in various batch sizes with minimal changeover time thanks to innovative technology like the flexible manufacturing system (FMS). The interval-valued MCDM method (Mathew and Thomas, 2019), preference selection index method (Maniya and Bhatt, 2011), MACBETH (Karande and Chakraborty, 2013), and combinatorial mathematics-based decision-making method (Rao and Parnichkun, 2009) are just a few examples of the MCDM techniques that have previously been used by many researchers to select an appropriate FMS from a variety of alternatives. But there is still a need for an effective scientific decision-making method that can quantify ambiguous human preferences. This study recommends integrating SFS with AHP and TOPSIS as a result. This work considers a real-world industrial decision-making scenario presented by Kulak and Karaman (2005), in which a tractor component manufacturer desires to upgrade their manufacturing system. The proposed MCDM technique is to be statistically validated in this paper. They evaluated four distinct FMS based on six evaluation criteria, as given in Table 1. Expert consensus decision-making produced Table 1.FMS-1, the best option, and FMS-2, the second-best option, can replace spherical fuzzy AHP-TOPSIS and all other MCDM techniques [25]

Annual depreciation and maintenance costs (ADM): Using asset life estimates and rules approved by the Authority, yearly depreciation refers to the systematic annual depreciation of assets included in the Depreciated Asset Value that is dispersed across the useful lifespan of those assets. The word maintenance expense refers to any costs made by a person or corporation to keep their assets in good functioning order. The depreciated asset value for 2006 shall be amortised over a 40-year asset life on a straight-line basis. These costs could be applied to maintenance tasks like putting antivirus software on computers or to repairs like fixing a car or piece of machinery.

Quality of results (Q): The phrase "quality of results" (QoR) is used to assess technical processes. The most common representation is a vector of components, with the specific case of a synthetic measure for a single dimension.
Ease of use (E): A fundamental idea that outlines how simple it is for customers to utilize a product is ease of use. The goal of design teams is to maximize usability while providing the most functionality and taking into account business constraints. For example, "Users must be able to tap Find within 3 seconds of accessing the interface."
Competitiveness (C): Competitiveness in business refers to an organization's capacity to strike a favourable balance between the calibre and cost of its products and services.
Adaptability (A): The ability to quickly pick up new information and behaviours in response to change circumstances is referred to as adaptability, a soft skill. Flexibility is a quality that businesses commonly look for when hiring new employees because it is necessary for progress within a role.
Expandability (Ex): The term "expandability" describes a computer system's capacity to accept upgrades to its features or capabilities. Expandability in terms of hardware could include adding additional or larger hard drives, more memory, or a quicker dedicated graphics chip.

3. WSM METHOD

The WSM approach, also known as the Weighted Sum Model, is a multi-criteria analysis decision-making method. It entails giving several criteria weights and computing the weighted total of every alternative option based on these weights. Here's a general outline of the WSM method:
1. Identify Criteria: Establish the standards by which the alternatives will be assessed. These standards must reflect the important variables to take into account and be pertinent to the issue at hand.
2. Assign Weights: Give each criterion a weight based on how important or urgent it is to you. The decision-maker's preferences or priorities are reflected in the weights. All weights added together should equal 1, or 100%.
3. Evaluate Alternatives: Assign scores or ratings based on how each choice compares to each criterion. Depending on the nature of the criterion and the data at hand, the evaluation may be either qualitative or quantitative.
4. Normalize Scores: Normalize the scores obtained for each criterion. This step ensures that the scores are on a comparable scale, regardless of the criteria's different units or measurement scales. This can be done by dividing each score by the maximum possible score for that criterion.
5. Calculate Weighted Sum: Multiply the normalized scores for each alternative by their corresponding weights. Then, sum up these weighted scores for each alternative.
6. Rank Alternatives: Rank the alternatives according to their combined weighted sum. According to the criteria and their given weights, the alternative with the highest weighted sum is the best option.
The WSM method provides a systematic approach to evaluate and rank alternatives based on multiple criteria, taking into account the decision-makers preferences. By assigning weights and calculating the weighted sum, it allows for a comprehensive analysis of the available options and helps in making informed decisions.

4. RESULT AND DISCUSSION

TABLE 1. DATA SET

DATA SET						
FMS	Quality of results (Q)	Ease of use (E)	Competitiveness (C)	Adaptability (A)	Expandability (Ex)	Annual depreciation and maintenance costs
FMS-1	0.955	0.59	0.955	0.59	0.59	0.665
FMS-2	0.59	0.5	0.59	0.59	0.59	0.135
FMS-3	0.5	0.5	0.59	0.955	0.5	0.41
FMS-4	0.335	0.5	0.59	0.59	0.5	0.255

In this data collection, various Flexible Manufacturing Systems (FMS) are assessed according to various criteria, as shown in Table 1. Quality of results (Q), Usability (E), Competitiveness (C), Adaptability (A), Expandability (Ex), and Annual Depreciation and Maintenance Costs (ADM) are among the criteria. For each FMS, numerical scores are assigned to each criterion, representing the evaluation of that FMS with respect to the specific criterion. The scale goes from 0 to 1, with 1 being the best performance or quality.

TABLE 2. WSM Weighted Sum Model

WSM Weighted Sum Model						
FMS	Quality of results (Q)	Ease of use (E)	Competitiveness (C)	Adaptability (A)	Expandability (Ex)	Annual depreciation and maintenance costs
FMS-1	1.00000	1.00000	1.00000	0.61780	1.00000	0.20301
FMS-2	0.61780	0.84746	0.61780	0.61780	1.00000	1.00000
FMS-3	0.52356	0.84746	0.61780	1.00000	0.84746	0.32927
FMS-4	0.35079	0.84746	0.61780	0.61780	0.84746	0.52941

Table 2 shows in this data set, the Weighted Sum Model (WSM) are applied to evaluate Flexible Manufacturing Systems (FMS) based on various criteria. The criteria considered include Quality of results (Q), Ease of use (E), Competitiveness (C), Adaptability (A), Expandability (Ex), and Annual depreciation and maintenance costs. Each FMS is assigned numerical scores for each criterion, representing the evaluation of that FMS with respect to the specific criterion. The scale goes from 0 to 1, with 1 being the best performance or quality.

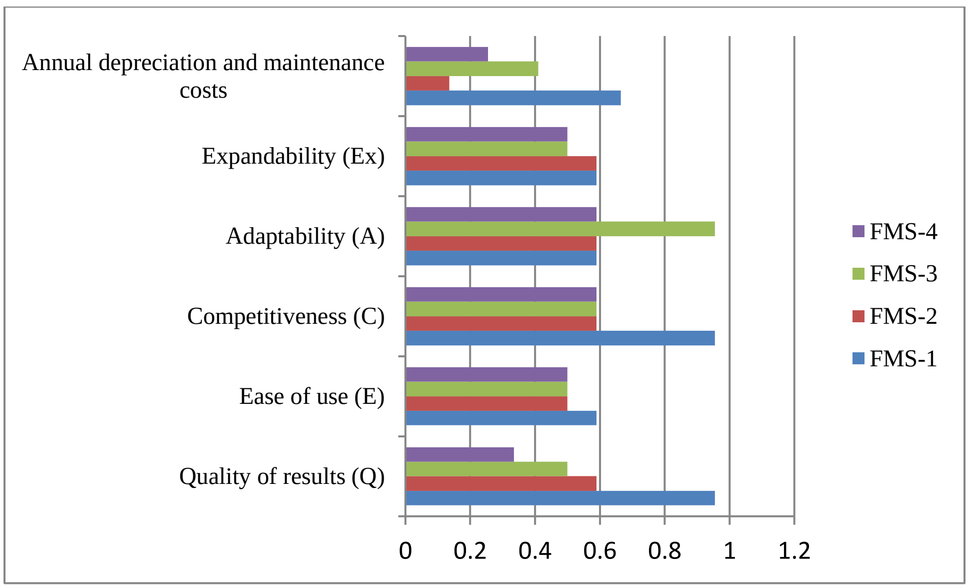

FIGURE 1. WSM Weighted Sum Model

The Weighted Sum Model (WSM) is used in this data set to evaluate Flexible Manufacturing Systems (FMS) based on a number of criteria, as shown in Figure 2. Quality of results (Q), Ease of usage (E), Competitiveness (C), Adaptability (A), Expandability (Ex), and Annual depreciation and maintenance expenses are among the parameters taken into account. Each FMS is assigned numerical scores for each criterion, representing the evaluation of that FMS with respect to the specific criterion. The scores range from 0 to 1, with 1 indicating the highest performance or characteristic.

TABLE 3. Weight

Weight						
FMS	Quality of results (Q)	Ease of use (E)	Competitiveness (C)	Adaptability (A)	Expandability (Ex)	Annual depreciation and maintenance costs
FMS-1	0.16	0.16	0.16	0.16	0.16	0.16
FMS-2	0.16	0.16	0.16	0.16	0.16	0.16
FMS-3	0.16	0.16	0.16	0.16	0.16	0.16
FMS-4	0.16	0.16	0.16	0.16	0.16	0.16

Weights are displayed in Table 3 for each criterion in the evaluation of Flexible Manufacturing Systems (FMS). The criteria considered include Quality of Results (Q), Ease of Use (E), Competitiveness (C), Adaptability (A), Expandability (Ex), and Annual Depreciation and Maintenance Expenses. Each weight represents the relative importance or priority of the corresponding criterion. In this case, all weights are set to 0.16, indicating that the decision-maker considers each criterion equally important in the evaluation process.

TABLE 4. Weighted normalized decision matrix

Weighted normalized decision matrix						
FMS	Quality of results (Q)	Ease of use (E)	Competitiveness (C)	Adaptability (A)	Expandability (Ex)	Annual depreciation and maintenance costs
FMS-1	0.16000	0.16000	0.16000	0.09885	0.16000	0.03248
FMS-2	0.09885	0.13559	0.09885	0.09885	0.16000	0.16000
FMS-3	0.08377	0.13559	0.09885	0.16000	0.13559	0.05268
FMS-4	0.05613	0.13559	0.09885	0.09885	0.13559	0.08471

Table 4 offers a weighted normalized decision matrix for assessing Flexible Manufacturing Systems (FMS) based on various factors. The characteristics considered include Quality of Results (Q), Ease of Use (E), Competitiveness (C), Adaptability (A), Expandability (Ex), and Annual Depreciation and Maintenance Expenses. This weighted normalized decision matrix provides a comprehensive overview of the relative performance of each FMS option across the criteria considered. It forms a basis for further analysis, such as calculating the weighted sum for each FMS option based on the assigned weights and criterion scores, to determine the overall ranking or preference of the FMS alternatives.

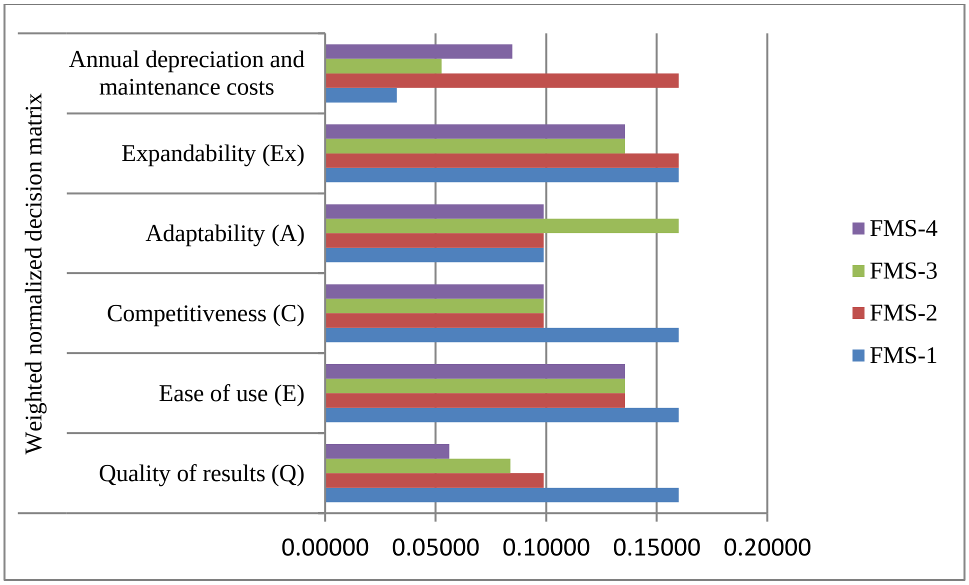

FIGURE 2. Weighted normalized decision matrix

The weighted normalized decision matrix that is proposed for evaluating Flexible Manufacturing Systems (FMS) in line with various criteria is shown in Figure 2. The characteristics considered include Quality of Results (Q), Ease of Use (E), Competitiveness (C), Adaptability (A), Expandability (Ex), and Annual Depreciation and Maintenance Expenses.. This weighted normalized decision matrix provides a comprehensive overview of the relative performance of each FMS option across the criteria considered. It forms a basis for further analysis, such as calculating the weighted sum for each FMS option based on the assigned weights and criterion scores, to determine the overall ranking or preference of the FMS alternatives.

TABLE 5. Preference Score

FMS	Preference Score
FMS-1	0.77133
FMS-2	0.75214
FMS-3	0.66649
FMS-4	0.60971

Table 5 shows the FMS preference scores are provided for each Flexible Manufacturing System (FMS) option. The preference scores represent the overall evaluation or preference of each FMS option based on the criteria and their respective weights. The preference scores are calculated by summing the weighted contribution of each criterion for each FMS option, as determined by the weighted normalized decision matrix. The higher the preference score, the more favorable the FMS option is considered. According to the provided data, FMS-1 has a preference score of 0.77133, FMS-2 has a preference score of 0.75214, FMS-3 has a preference score of 0.66649, and FMS-4 has a preference score of 0.60971. These scores indicate the relative ranking or preference of the FMS options, with FMS-1 being the most preferred option and FMS-4 being the least preferred option based on the evaluation criteria and weights used in the analysis.

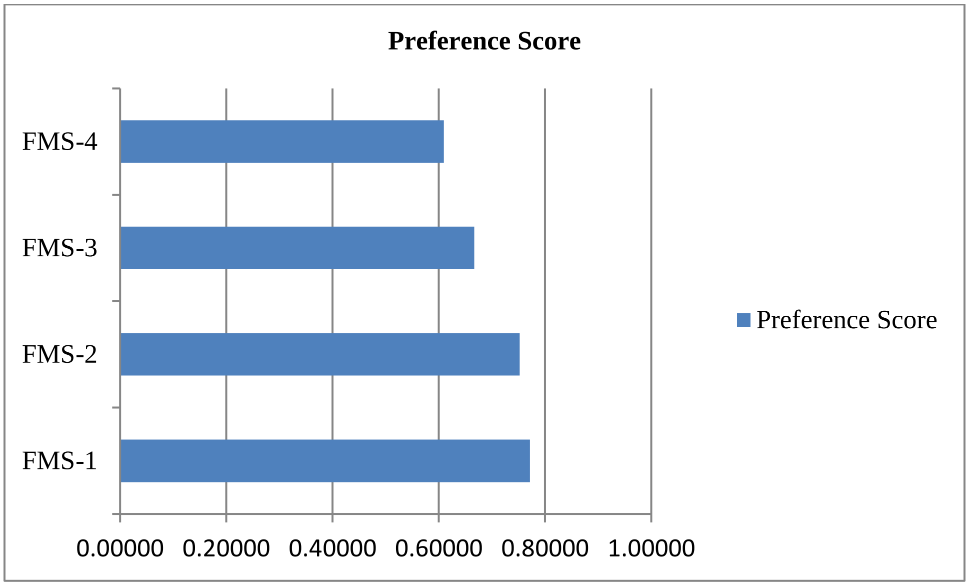

FIGURE 3. Preference Score

The FMS preference scores for each Flexible Manufacturing System (FMS) option are shown in Figure 3. Based on the criteria and their corresponding weights, the preference scores show how each FMS option has been rated overall. The preference scores are calculated by summing the weighted contribution of each criterion for each FMS option, as determined by the weighted normalized decision matrix. The higher the preference score, the more favorable the FMS option is considered. According to the provided data, FMS-1 has a preference score of 0.77133, FMS-2 has a preference score of 0.75214, FMS-3 has a preference score of 0.66649, and FMS-4 has a preference score of 0.60971

TABLE 6. Rank

FMS	Rank
FMS-1	1
FMS-2	2
FMS-3	3
FMS-4	4

In this table 6 data set, the ranks are provided for each Flexible Manufacturing System (FMS) option. The ranks represent the relative ordering or position of each FMS option based on their evaluation or performance. According to the provided data, FMS-1 has been assigned the rank of 1, indicating that it is ranked first among the FMS options. FMS-2 has the rank of 2, FMS-3 has the rank of 3, and FMS-4 has the rank of 4. These ranks signify the ordering of the FMS options, with FMS-1 being the highest-ranked option and FMS-4 being the lowest-ranked option.

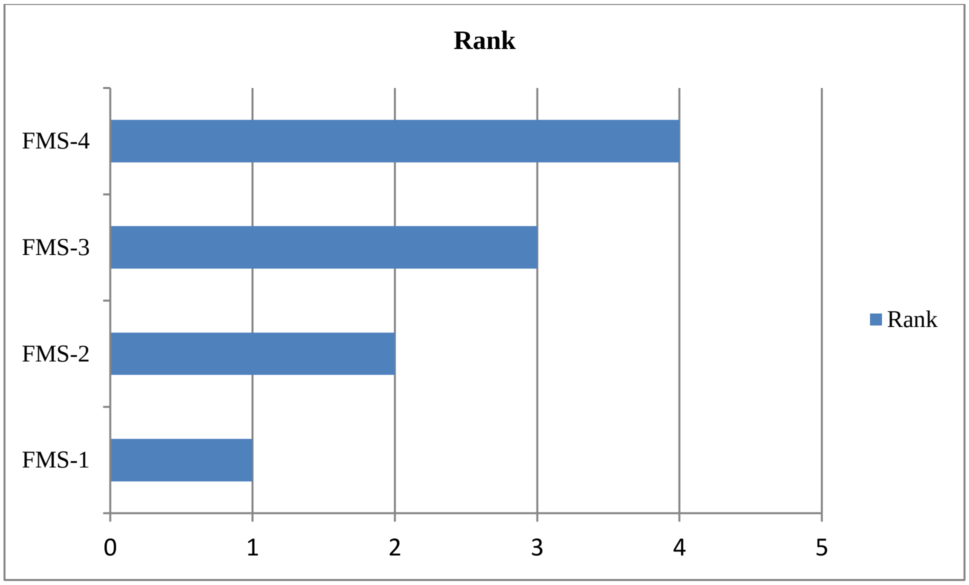

FIGURE 4. Rank

In this figure 4 data set, the ranks are provided for each Flexible Manufacturing System (FMS) option. The ranks represent the relative ordering or position of each FMS option based on their evaluation or performance. According to the provided data, FMS-1 has been assigned the rank of 1, indicating that it is ranked first among the FMS options. FMS-2 has the rank of 2, FMS-3 has the rank of 3, and FMS-4 has the rank of 4. These ranks signify the ordering of the FMS options, with FMS-1 being the highest-ranked option and FMS-4 being the lowest-ranked option.

5. CONCLUSION

In conclusion, the integration of AI with Flexible Manufacturing Systems offers numerous opportunities for enhanced operational efficiency, productivity, and adaptability. Leveraging AI technologies in planning and scheduling, intelligent control, and predictive maintenance enables FMS to optimize resource utilization, respond effectively to changing demands, and mitigate unplanned downtime. However, challenges related to data availability, system complexity, and human-machine interaction must be addressed to fully unlock the potential of AI in FMS. Overcoming these challenges through research, technological advancements, and collaboration between academia and industry will pave the way for the widespread adoption of AI-enabled FMS and drive the transformation of manufacturing towards intelligent and flexible production systems. Additionally, AI-powered FMS can provide valuable insights through advanced analytics, enabling manufacturers to identify patterns, trends, and opportunities for process improvement. This data-driven approach supports decision-making, facilitates continuous optimization, and helps achieve cost savings.

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