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Comparative assessment of flexible manufacturing systems using the EDAS and Shannon entropy method

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Abstract. As global competition intensifies, most manufacturing companies strive to improve their production methods to gain a competitive edge. One such advancement is the adoption of Flexible Manufacturing Systems (FMS), which enable the efficient production of various products in specified quantities with minimal lead times. These systems offer adaptability and efficiency, allowing manufacturers to leverage modern technologies to improve operational performance. However, evaluating or selecting an appropriate FMS involves considering numerous conflicting criteria. To address this complexity, Multi-criteria Decision Making (MCDM) methods are employed. This study conducts a comparative evaluation of eight FMS alternatives using the Evaluation based on the Distance from the Average Solution (EDAS) method, integrated with Shannon Entropy for objective weight determination. Key performance indicators, including production cost, system flexibility, energy efficiency, and operational reliability, are used in the assessment. The Shannon Entropy method ensures unbiased, data-driven weight assignment, while the EDAS method provides a robust framework for ranking alternatives based on their deviation from an average solution. To test the robustness of the ranking, we compared the ranking with other MCDM methods and also conducted a sensitivity analysis using equal weighting criteria. We found that the first and last rankings remained unchanged when we changed the criteria, although there were slight changes in the rankings of some alternatives. The findings highlight the effectiveness of integrating EDAS with Shannon Entropy in selecting the best flexible manufacturing systems, offering valuable insights for manufacturers and decision-makers.

Keywords: EDAS method, flexible manufacturing systems, multi-criteria decision making, normalization, shannon's entropy method

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1. Introduction

In the present time, due to increasing global competition, manufacturing companies need advanced production technologies such as computer-controlled machines, automatic material handling systems, and FMS to quickly meet customer needs and gain a competitive advantage in the global market. With the spread of advanced technology, FMS has attracted the attention of many manufacturing companies, and many companies have switched to this system. The FMS is composed of machine tools and/or robots linked by a transport network and controlled by a central computer to move parts and/or tools as suggested in [17]. The term 'flexible' refers to

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the system's ability to process different types of parts simultaneously at various workstations, with the capability to easily adjust the mix of part types and production quantities in response to changing demand. Potential benefits of using FMS include reducing stock levels, production lead time, installation costs, and providing high flexibility and quality.

The FMSs are systems that can produce various products in the desired quantity in a short time. Therefore, having FMS has become a necessity for many manufacturers. In addition, since the installation of FMS requires a large investment, the selection of the most suitable FMS requires comprehensive analysis and evaluation [5]. Therefore, to get the most benefit from the system in the selection of FMS, a detailed criteria scan must be made, and the importance of these criteria must be determined correctly. If some of these criteria conflict with each other, measurement becomes difficult, and a balance must be established between these criteria when considering the preferences of the decision-makers in the production enterprise. Since many criteria are included in the selection phase of FMS, the MCDM method has been used many times in the literature on FMS selection.

Some of the MCDM methods used for FMS selection in the literature are as follows. The weight of the criteria can be calculated by the AHP method [4, 2]. Another axiomatic design method is discussed in the literature [19], where the author used the Entropy method to determine the criterion weights, and they call preference ranking methods such as EVAMIX (Evaluation of Mixed Data), COPRAS (Complex Proportional Assessment), ORESTE (Organization, Rangement Et Synthese De Donnes Relationnelles), OCRA (Operational Competitiveness Rating), and EDAS in ranking the FMSs. The DEMATEL (Decision-Making Trial and Evaluation Laboratory) method was used to find the relationship density between the criteria and calculate the weight of the criteria. The DEMATEL method evaluated decisions about whether or not to install FMS. Some study evaluated the flexible production systems by combining heuristic fuzzy logic and multi-attribute group decision-making methods [13].

2. Literature review

The discipline of production management is relevant to this study. As the study [16] state that the core components of field material handling systems include computer numerical control machine tools, which are loaded and unloaded, along with automated material handling devices by advanced industrial robots, computer-controlled storage and retrieval systems, and other automated equipment. According to [6], FMS issues are divided into four categories: design, planning, scheduling, and control. The right amount of each type of machine tool, the capacity handling system of the material, and the buffer size are among the design issues with FMSs. Planning issues in FMSs include choosing which parts to process at the same time, grouping machine tools optimally, assigning operations to different components, and assigning pallets and fixtures to different part types. Finding the ideal order for machine tools and components as input sequences is one of the scheduling issues associated with FMSs. Monitoring the system to make sure that requirements and deadlines are followed and that unreliability issues are taken into account is known as FMS control problems [22, 6]. The design challenge is the main topic of the study that is being suggested in this paper.

Prior research has concentrated on machine flexibility and routing, which affect several performance metrics. Productivity enhancement, machine selection, number allotted, capacity, buffer sizes, pallet allocations, material handling systems, jigs and fixtures allocations, FMS planning, scheduling, optimization of limited resources, and FMS controls are among the issues associated with FMSs [20]. The increasing complexity and competitiveness of global manufacturing systems have prompted researchers to adopt MCDM approaches for evaluating flexible and sustainable production alternatives. Together, these studies demonstrate the adaptability and effectiveness of MCDM methods across a variety of domains, including trade, cybersecurity, sustainable manufacturing, and workforce development. Their collective insights support the use of MCDM—particularly integrated approaches like EDAS with Shannon Entropy—in the comparative evaluation of FMS under complex and dynamic decision environments.

Based on the aforementioned investigations, researchers have identified several elements that have a major influence on the performance of FMSs. The researchers include a variety of topics, including the need for design modifications in the final product, cutting circumstances, worker skill and adaptability, sequencing flexibility, routing flexibility, part sequencing, and determining the maximum number of routes. MCDM techniques, such as Fuzzy COPRAS or EDAS, have been used in several studies to assess the impact of compelling factors and variables on the performance of flexible manufacturing systems. Furthermore, to find the ideal value of variables and improve the overall performance of flexible manufacturing systems, further research has concentrated on optimization or simulation-based optimization techniques. Statistical analysis is the main tool which are utilized by other researchers, such as [3], to evaluate the impact of various variables and factors on FMS performance. By using a hybrid framework that combines MCDM, Entropy, and EDAS simulation, the suggested framework achieves all of these goals. The stated goals and possible capabilities are demonstrated by applying this technique to an actual industrial case study.

This paper introduces a very elaborate framework of decision-making involving the validation and prioritizing of Flexible Manufacturing Systems by unearthing the EDAS procedure with the Shannon Entropy technique to find objective weights. The Shannon Entropy approach generates a data-driven, step-by-step process by which it becomes possible to determine the relative importance of criteria through the use of inherent information variability within the data set. With the combination of EDAS, which assesses the alternatives based on positive and negative distances to an average solution, the suggested methodology can provide a strong framework to assess FMS that is transparent and objective. The main value of the current work is the use of this hybrid method on real FMS data and proving its practical value and its computational efficiency. The method will allow decision-makers to deal with multi-criteria analysis where the economic and technical aspects of the projects conflict (e.g., labor cost, quality improvement, floor area, capital cost). To show the robustness of the proposed EDAS Entropy framework, we compared it with existing MCDM methods such as COPRAS and the SWEI (Sum Weghted Exponential Information) MCDM methods. The similarity of orderings of the methods proves the reliability and soundness of the suggested method. Some of the major strengths are ease of implementation, lower computational complexities than pairwise-based methods, objective weight assignment, and stability or high ranking, irrespective of the weighting schemes employed. The above advantages turn the given approach into a useful instrument to be used to address the issue of selecting FMS and other complicated decision-making tasks in the manufacturing and industrial fields.

This study employs the entropy and EDAS method for selecting an FMS. Its originality lies in the fact that the entropy and EDAS methods have not previously been applied to FMS selection. Given that the decision matrix was already known, the Entropy method was utilized to determine the objective weights. The CRITIC (CRiteria Importance Through Inter-criteria Correlation) method, which is another method of finding objective weights, was not preferred in this study because it requires more processing. In MCDMs such as PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) and ELECTRE (Elimination and Choice Translating Reality), increasing the number of alternatives increases the processing time. Even though the number of alternatives increases in the ROV (Range of value) method, the processing time is very short compared to these methods since pairwise comparison is not made. Therefore, the EDAS method was preferred in this study.

3. Research methodology

The study methodology's goal is to offer an organized and methodical process for choosing the best FMS by utilizing the entropy and EDAS techniques. The methodology seeks to integrate both qualitative and quantitative criteria to ensure a comprehensive evaluation of FMS alternatives. By leveraging entropy for determining objective weights, it ensures impartiality in assigning importance to each criterion, minimizing biases from subjective judgments. The primary goal is to enhance decision-making accuracy in FMS selection by addressing multiple conflicting factors, such as cost, efficiency, flexibility, and technological compatibility. Additionally, the methodology aims to demonstrate the effectiveness of the entropy-based EDAS method in real-world applications, validating its utility in complex industrial environments. This approach provides a replicable and transparent framework for decision-makers in manufacturing industries to optimize their systems and improve productivity. Ultimately, it seeks to fill the gap in existing research by applying the EDAS MCDM method for FMS selection. Finally, COPRAS and SWEI MCDM methods are used to check the robustness of the ranking.

3.1. The Shannon's entropy method

To enhance objectivity in the evaluation process, objective weighting methods such as Shannon entropy are often integrated with MCDM techniques. The Shannon entropy method assigns weights to decision criteria based on the degree of variability in the data, reducing human bias and ensuring a data-driven evaluation. Information uncertainty is quantified using the idea of entropy. Information entropy [15] is a measure of how disordered a system is and how much valuable information can be extracted from the available data. Numerous papers have employed the weighted entropy method to resolve MCDM issues. The combined PROMETHEE and Entropy methods is applied for supplier selection [25]. The entropy method is used for calculating the criterion weight in many studies [7, 8, 9, 10, 11, 12]. Another study [1], the Entropy and VIKOR (VIekriterijumsko KOmpromisno Rangiranje) methods is used for sustainable strategy selection for SMEs.

The entropy method can be summarized in 5 steps [21]:

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

$$DM_{i,j} = [a_{i,j}]_{m\times n} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{bmatrix}. \tag{1}$$

In the equation (1), $a_{i,j}$ represents the performance in the criterion. This decision matrix includes a total of $j = 1, 2, 3, ...n$ criteria and $i = 1, 2, 3, ...m$ alternatives.

Step 2: The values in the decision matrix are standardized using equation (2) for the beneficial criteria, and equation (3) for the non-beneficial criteria. $r_{i,j}$ values in the equations shows the standardized version of the $a_{i,j}$ value.

$$r_{i,j} = \frac{a_{i,j}}{\max a_{i,j}}, \tag{2}$$

$$r_{i,j} = \frac{\min a_{i,j}}{a_{i,j}}. \tag{3}$$

Step 3: Standardized values are normalized using equation (4), where $s_{i,j}$ shows the normalized value.

$$s_{i,j} = \frac{r_{i,j}}{\sum_{i=1}^{m} r_{i,j}}. \tag{4}$$

Step 4: After the normalization process, the entropy value of each criterion is obtained using equation (5). The value of H_j represents the entropy of the j criterion.

$$H_j = -\frac{\sum_{j=1}^{n} s_{i,j} \log_2 s_{i,j}}{\log_2 m}. \tag{5}$$

Step 5: In the last step, the weight of each criterion is obtained.

$$w_j = \frac{1 - H_j}{\sum_{j=1}^{n} 1 - H_j}. \tag{6}$$

The value of w_j in equation (6) represents the objective weight of the criterion is represented. Through the application of the entropy method, these objective criterion weights are determined. After the last step of this method, the EDAS method is used, and the objective weights found by this method are transferred to rank the alternatives.

3.2. The EDAS method

The EDAS is an MCDM method used to assess and rank alternatives across various criteria. This method assesses how close or far an alternative is from an average solution, considering both positive and negative distances from the average. Evaluating and selecting appropriate FMS alternatives is inherently complex, involving multiple, often conflicting criteria such as cost, flexibility, reliability, and energy efficiency. To address this complexity, MCDM methods have been increasingly employed in manufacturing system evaluations. Among these methods, the EDAS approach has gained attention due to its simplicity, computational efficiency, and ability to consider both positive and negative deviations from an average solution [14]. This method evaluates and selects the suppliers based on criteria such as quality, cost, and delivery time. This prioritizes projects or tasks considering factors like cost, benefit, risk, and time. Distributing resources effectively among competing projects or departments. Assessing policy options based on social, economic, and ecological criteria. Choosing the best product design considering multiple factors like cost, functionality, and customer preference.

The EDAS method is a powerful tool for decision-makers dealing with complex scenarios involving multiple criteria. Its ability to provide a balanced evaluation of alternatives, simplicity, and robustness make it a popular choice in various fields. The EDAS technique was utilized to compute the performance of alternatives and then rank the alternatives. The EDAS technique consists the following steps [26].

Step 1: In this step, determining the average solutions of the matrix (AV_j) is formed by taking the average solutions of the criteria.

$$AV = [AV_j]_{1\times m}. \tag{7}$$

Where AV_j represents the average of criterion j and is calculated as:

$$AV_j = \frac{\sum_{i=1}^{n} a_{i,j}}{n}. \tag{8}$$

Step 2: For each criterion, calculate the positive distance from average (PDA) as well as the negative distance from average (NDA) from the average by using (9) and (10), and then matrices are obtained. Based on whether the objective is benefit-based or cost-based, various equations are used to compute each element of the generated matrices ($PDA_{i,j}, NDA_{i,j}$).

$$PDA = [PDA_{i,j}]_{n\times m}, \tag{9}$$

$$NDA = [NDA_{i,j}]_{n\times m}. \tag{10}$$

If j-th criterion is beneficial, the values of $PDA_{i,j}$ and $NDA_{i,j}$ are calculated as:

$$PDA_{i,j} = \frac{\max\left(0, (a_{i,j} - AV_j)\right)}{AV_j}, \tag{11}$$

$$NDA_{i,j} = \frac{\max\left(0, (AV_j - a_{i,j})\right)}{AV_j}. \tag{12}$$

Similarly, if j-th criterion is non-beneficial, the values of $PDA_{i,j}$ and $NDA_{i,j}$ are calculates as:

$$PDA_{i,j} = \frac{\max\left(0, (AV_j - a_{i,j})\right)}{AV_j}, \tag{13}$$

$$NDA_{i,j} = \frac{\max\left(0, (a_{i,j} - AV_j)\right)}{AV_j}. \tag{14}$$

Step 3: With the help of the following equations (15) and (16) the weighted positive value (SP_i) and weighted negative values (SN_i) are calculated respectively. The equation is multiplied by the weight of the criteria computed by using Shannon's entropy method, i.e.

$$SP_i = \sum_{j=1}^{n} w_j PDA_{i,j}, \tag{15}$$

$$SN_i = \sum_{j=1}^{n} w_j NDA_{i,j}. \tag{16}$$

Step 4: In this step, the weighted positive value of SP_i and weighted negative value SN_i are normalized as:

$$NSP_i = \frac{SP_i}{\max_i\left(SP_i\right)}, \tag{17}$$

$$NSN_i = 1 - \frac{SN_i}{\max_i\left(SN_i\right)}. \tag{18}$$

Step 5: Finally, for each alternative, the appraisal scores (AS_i) are evaluated as follows:

$$AS_i = \frac{1}{2}(NSP_i + NSN_i). \tag{19}$$

Alternative appraisal score (AS_i) lies in the range $0 \leq AS_i \leq 1$, where the higher the value, the closer the alternative is to the ideal (average-based) choice.

3.3. The SWEI method

The SWEI MCDM was developed by [8]. It is very useful in the decision-making domain, i.e. there are many theoretical mplications of SWEI in the MCDM. The model enhances the accuracy and robustness of decision-making processes by effectively handling criterion interdependencies and uncertainties. The SWEI offers significant advantages in modelling interdependencies and handling uncertainty; it is essential to consider the potential complexity it introduces to MCDM models. The integration of SWEI requires advanced computational techniques and a deep understanding of the underlying decision-making context, which results in its effective application in solving complex problems. This complexity must be managed to prevent it from becoming a barrier to practical implementation. The fundamental principle of the SWEI method is that alternatives with higher information content receive lower preference rankings, whereas those with lower information content are assigned higher ranks. This is based on the inverse relationship between the probability of an alternative and its associated information content—fewer probable alternatives (i.e., more uncertain or diverse in performance) convey greater informational entropy, thus indicating less desirability in the decision-making context. The following are the steps involved in SWEI MCDM [7, 8]:

Step 1: Construct the information decision matrix $IDM = [a_{i,j}]_{m\times n}$ according to (20), where $a_{i,j} > 0$:

$$IDM_{i,j} = [a_{i,j}]_{m\times n} = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{bmatrix}. \tag{20}$$

Step 2: Normalize the decision matrix for beneficial and non-beneficial criteria according to (21) and (22):

$$\overline{IDM}_{i,j} = \frac{a_{i,j}}{\sum_{i=1}^{m} a_{i,j}}, \quad \text{beneficial criteria,} \tag{21}$$

$$\overline{IDM}_{i,j} = \frac{1/a_{i,j}}{\sum_{i=1}^{m} 1/a_{i,j}}, \quad \text{non-beneficial criteria.} \tag{22}$$

Step 3: Compute the information score ($IS_{i,j}$) of the attributes of the normalized decision matrix for the alternatives according to (23):

$$IS_{i,j} = \log_2\left(\frac{1}{\overline{IDM}_{i,j}}\right). \tag{23}$$

Step 4: Compute the weighted exponential information score of the decision matrix (IDM''_i) for the alternatives according to (24):

$$SWEI = IDM''_i = \sum_{j=1}^{n}\left(\log_2\left(\frac{1}{\overline{IDM}_{i,j}}\right)\right)^{w_j}, \tag{24}$$

where w_j is the weight of the criterion such that $\sum_{j=1}^{n} w_j = 1$.

Step 5: Finally, the summing the weighted exponential information scores for all alternatives and sorted in ascending order to establish the final preference ranking. The alternative with the lowest score is designated the first rank.

3.4. The COPRAS method

The COPRAS MCDM was introduced by [23]. It stands out as an MCDM technique used to analyze and rank a series of alternatives based on a set of conflicting criteria. It is especially useful where there is a need to both maximize and minimize. The COPRAS enables us to evaluate the alternatives with direct proportional measurement based on the criteria's meanings (weights) and ideas of how each alternative performs compared with the ideal one. A process entails the normalization of the decision matrix, the use of weightings, and the calculation of both the sums of beneficial (maximizing) and non-beneficial (minimizing) criteria of different alternatives. The following are the steps involved in COPRAS:

Step 1: Construct the decision matrix $DM = [a_{i,j}]_{m\times n}$ according to (20)

Step 2: Normalize the decision matrix according to (25):

$$s_{i,j} = \frac{a_{i,j}}{\sum_{i=1}^{m} a_{i,j}}. \tag{25}$$

Step 3: Compute the weighted normalized decision matrix for the alternatives using:

$$r_{i,j} = s_{i,j} \times w_j, \tag{26}$$

where w_j is the weight of the criterion and $\sum_{j=1}^{n} w_j = 1$.

Step 4: Compute the sums of weighted normalized values for each alternative for beneficial (maximizing) criteria and non-beneficial (minimizing) criteria by (27) and (28), respectively.

$$S_i^+ = \sum_{j=1}^{n} r_{i,j}, \quad \text{beneficial criteria}, \tag{27}$$

$$S_i^- = \sum_{j=1}^{n} r_{i,j}, \quad \text{non-beneficial criteria}. \tag{28}$$

Step 5: Compute the relative significance for the alternatives according to (29):

$$Q_i = S_i^+ + \frac{\min S_i^- \sum_{i=1}^{m} S_i^-}{S_i^- \sum_{i=1}^{m} \left(\frac{\min S_i^-}{S_i^-}\right)}. \tag{29}$$

Step 6: Compute the utility degree (%) for the alternatives according to (30):

$$U_i = \frac{Q_i}{\max Q_i} \times 100\%. \tag{30}$$

The alternative with the highest utility degree U_i is considered the most preferable. COPRAS is valued for its simplicity, transparency, and capacity to handle conflicting objectives in decision-making processes.

4. Results and discussion

FMS is an innovative manufacturing system that manage and create a wide range of products with minimum operator interaction. It combines automated material handling systems, centralized control systems, and computer-controlled equipment to achieve high levels of flexibility and productivity. FMS allows for the production of different models and variants of the same production line without significant downtime or reconfiguration. It ensures components and subassemblies are produced in sync with demand, reducing inventory costs and improving efficiency. It is capable of producing various electronic products, such as smartphones and laptops, which require frequent design changes and updates. Industries with high customization, quick adaptability, and efficient production traditionally use FMS. FMS system is particularly useful in automotive manufacturing, where multiple variants and parts have to be assembled on the same assembly line. This leads to seamless changes between design products without downtime, therefore increasing productivity and minimizing costs. FMS is used in electronics to support the rapid creation of circuit boards and components to meet evolving consumer requirements. Aerospace industries make use of FMS for manufacturing complex parts with precision, which helps ensure consistency and quality are assured.

4.1. Case study description

As industries worldwide adopt Industry 4.0 practices, research in FMS ensures that manufacturers stay competitive by leveraging the latest advancements in automation and digitalization. The FMS is enhancing the resilience of manufacturing systems to respond to global supply chain disruptions, fluctuating demands, and unforeseen challenges. In summary, FMS plays a crucial role in modern manufacturing, and ongoing research is essential to harness its full potential, ensuring adaptability, efficiency, and competitiveness in a rapidly evolving industrial landscape. In this study, the data is taken from [24] for the selection problem of an FMS. They identified seven criteria with eight alternatives for the FMS problem. These seven criteria are as follows; reduction in labor cost (C-1), the percentage reduction in installation cost (C-2), the percentage reduction in the amount of backlog between process steps (C-3), increase in market response (C-4), increase in quality (C-5), floor area in square meters (C-6), capital and maintenance cost in thousand dollars (C-7). Of these seven criteria, the first five criteria are beneficial (max), and the last two criteria are non-beneficial (min) criteria. The decision matrix is tabulated in Table 1.

Criteria →	C-1	C-2	C-3	C-4	C-5	C-6	C-7
Alternatives ↓	max	max	max	max	max	min	min
A-1	30	5	23	0.745	0.745	5000	1500
A-2	18	15	13	0.745	0.745	6000	1300
A-3	15	10	12	0.5	0.5	7000	950
A-4	25	13	20	0.745	0.745	4000	1200
A-5	14	14	18	0.255	0.745	3500	950
A-6	17	9	15	0.745	0.5	5250	1250
A-7	23	20	18	0.5	0.745	3000	1100
A-8	16	14	8	0.255	0.5	3000	1500

Table 1: *Decision matrix for selection of the best FMS.*

The decision matrix is standardized by applying the first step of the Entropy method from eq. (2) and (3) and is given in Table 2. The standardized decision matrix is normalized using eq. (4) an is given in Table 3.

Alternatives	C-1	C-2	C-3	C-4	C-5	C-6	C-7
A-1	1.000	0.250	1.000	1.000	1.000	0.600	0.633
A-2	0.600	0.750	0.565	1.000	1.000	0.500	0.731
A-3	0.500	0.500	0.522	0.671	0.671	0.429	1.000
A-4	0.833	0.650	0.870	1.000	1.000	0.750	0.792
A-5	0.467	0.700	0.783	0.342	1.000	0.857	1.000
A-6	0.567	0.450	0.652	1.000	0.671	0.571	0.760
A-7	0.767	1.000	0.783	0.671	1.000	1.000	0.864
A-8	0.533	0.700	0.348	0.342	0.671	1.000	0.633

Table 2: *Standardized decision matrix for the FMS.*

4.2. The EDAS is integrated with the Shannon entropy method

The entropy of each criterion is calculated using eq. (5), after normalization. The criterion weights are calculated using eq. (6). The weights of the criterion computed by the Entropy method are tabulated in the last row of Table 3. A graphical illustration of the criterion weight is given in Figure 1. The criteria are listed as follows according to their weights: $C-4 > C-2 > C-6 > C-3 > C-1 > C-5 > C-7$. The most significant criterion is C-4 (market response). After calculating the weights of the criteria, the EDAS method is used. In the first step, the average value (AV_j) of the decision matrix from Table 1 is determined. The average value is formed by taking the average solutions of the criteria in the normalization process. Next, the PDA and NDA are calculated from Table 3 by using eq. (9) and (10). Tables 4 and 5 show the values of PDM and NDM, respectively.

Alternatives	C-1	C-2	C-3	C-4	C-5	C-6	C-7
A-1	0.190	0.050	0.181	0.166	0.143	0.105	0.099
A-2	0.114	0.150	0.102	0.166	0.143	0.088	0.114
A-3	0.095	0.100	0.094	0.111	0.096	0.075	0.156
A-4	0.158	0.130	0.157	0.166	0.143	0.131	0.123
A-5	0.089	0.140	0.142	0.057	0.143	0.150	0.156
A-6	0.108	0.090	0.118	0.166	0.096	0.100	0.119
A-7	0.146	0.200	0.142	0.111	0.143	0.175	0.135
A-8	0.101	0.140	0.063	0.057	0.096	0.175	0.099
Average	19.8	12.5	15.9	0.56	0.65	4594	1219
Weights	0.121	0.213	0.149	0.256	0.060	0.150	0.050

Table 3: *Normalized decision matrix for the FMS.*

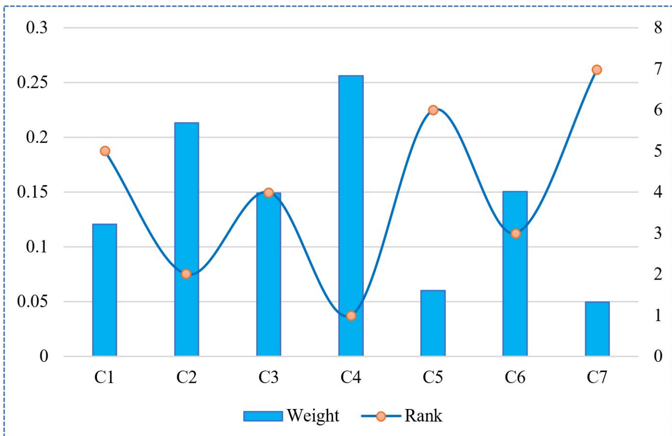

Figure 1: *Criterion weight score with ranking.*

Alternatives	C-1	C-2	C-3	C-4	C-5	C-6	C-7
A-1	0.519	0.000	0.449	0.327	0.141	0.000	0.000
A-2	0.000	0.200	0.000	0.327	0.141	0.000	0.000
A-3	0.000	0.000	0.000	0.000	0.000	0.000	0.221
A-4	0.266	0.040	0.260	0.327	0.141	0.129	0.015
A-5	0.000	0.120	0.134	0.000	0.141	0.238	0.221
A-6	0.000	0.000	0.000	0.327	0.000	0.000	0.000
A-7	0.165	0.600	0.134	0.000	0.141	0.347	0.097
A-8	0.000	0.120	0.000	0.000	0.000	0.347	0.000

Table 4: *Positive decision matrix from the average value.*

Finally, weighted positive values (SP_i), weighted negative values (SN_i), weighted positive normalized value (NSP_i), weighted negative normalized value (NSN_i), and appraisal scores (AS_i) are computed. Weighted normalized positive value represents the weighted contribution of how well an alternative performs above average. Weighted normalized negative values represent the weighted contribution of how poorly an alternative performs below average. Their graphical representation is shown in Figure 2. The final ranking of flexible manufacturing systems is shown in Table 6. Figure 3 illustrates the FMSs and their final ranking based on Entropy and EDAS techniques. Based on the results of the evaluation of the EDAS approach, the best

FMS for the particular application of the industrial work under the current parameters is A-7 followed by A-4, A-1, A-2, A-6, A-5, A-8 and A-3.

Alternatives	C-1	C-2	C-3	C-4	C-5	C-6	C-7
A-1	0.000	0.600	0.000	0.000	0.000	0.088	0.231
A-2	0.089	0.000	0.181	0.000	0.000	0.306	0.067
A-3	0.241	0.200	0.244	0.109	0.234	0.524	0.000
A-4	0.000	0.000	0.000	0.000	0.000	0.000	0.000
A-5	0.291	0.000	0.000	0.546	0.000	0.000	0.000
A-6	0.139	0.280	0.055	0.000	0.234	0.143	0.026
A-7	0.000	0.000	0.000	0.109	0.000	0.000	0.000
A-8	0.190	0.000	0.496	0.546	0.234	0.000	0.231

Table 5: *Negative decision matrix from the average value.*

Alternatives	SPi	SNi	NSPi	NSNi	ASi	Rank
A-1	0.222	0.153	0.951	0.418	0.685	3
A-2	0.135	0.087	0.578	0.668	0.623	4
A-3	0.011	0.229	0.047	0.127	0.087	8
A-4	0.192	0.000	0.823	1.000	0.911	2
A-5	0.101	0.175	0.432	0.334	0.383	6
A-6	0.084	0.122	0.359	0.536	0.448	5
A-7	0.233	0.028	1.000	0.893	0.947	1
A-8	0.078	0.262	0.333	0.000	0.167	7

Table 6: *Final ranking of the FMS by the EDAS method.*

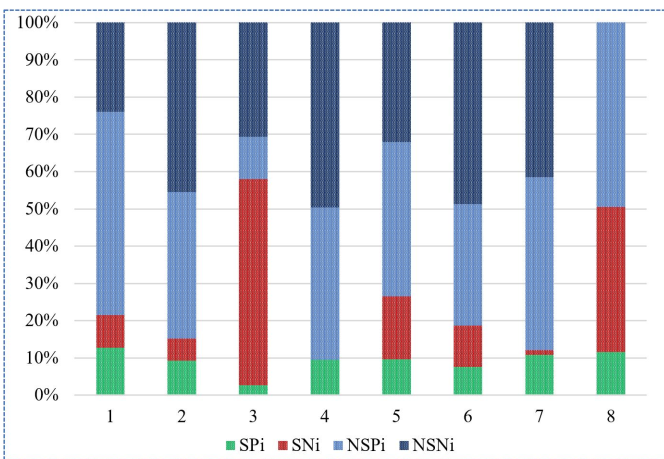

Figure 2: *Graphical representation of SP_i, SN_i, NSP_i and NSN_i.*

These outcomes are similar to those proposed by [24] with the fuzzy programming technique for multiple objectives. It should be noted, nevertheless, that the user's assessments of relative relevance determine the ranking. If the user gives the characteristics varying relative priority values, the ranking that is shown could be altered. This method is equivalent to the study [18]. The underlying concept is that criteria with higher variability (or more "entropy") contain more information and should be given more weight. In contrast, the approach presented in this work offers a clear-cut, rational, and basic process for solving the FMS selection problem.

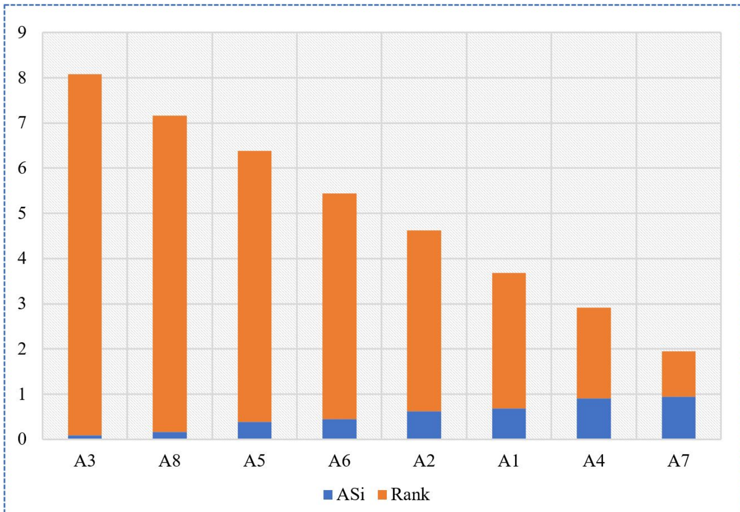

Figure 3: *Illustration of FMS ranking with the scores.*

4.3. Comparison with the SWEI and COPRAS

We further compare the robustness of the ranking generated by the EDAS method with the SWEI and COPRAS methods. Firstly, the decision matrix is constructed for SWEI and COPRAS according to eq. (20), in the first step from the raw data shown in Table 1. In the second step, the data is normalized using eq. (21) and (22) for the beneficial and non-beneficial criteria for SWEI and for COPRAS using eq. (24). The normalized values are tabulated in Table 7 for SWEI.

Alternatives	C-1	C-2	C-3	C-4	C-5	C-6	C-7
A-1	0.190	0.050	0.181	0.166	0.143	0.105	0.099
A-2	0.114	0.150	0.102	0.166	0.143	0.088	0.114
A-3	0.095	0.100	0.094	0.111	0.096	0.075	0.156
A-4	0.158	0.130	0.157	0.166	0.143	0.131	0.123
A-5	0.089	0.140	0.142	0.057	0.143	0.150	0.156
A-6	0.108	0.090	0.118	0.166	0.096	0.100	0.119
A-7	0.146	0.200	0.142	0.111	0.143	0.175	0.135
A-8	0.101	0.140	0.063	0.057	0.096	0.175	0.099

Table 7: *Normalized decision matrix by the SWEI for the FMS.*

In the third step eq. (23) is applied to rank the alternatives. Finally, in the fourth step, the alternatives are ranked in ascending order. Secondly, for the COPRAS method, the weighted normalized matrix is calculated by eq. (25), then the weighted normalized values are calculated by eq. (26) and (27) for the beneficial and the non-beneficial criteria, respectively. After calculating the relative importance for the alternatives by eq. (28), the utility degree is calculated by eq. (29). Afterwards, the alternative with the highest utility degree U_i is considered the most preferable. The ranking is shown in Table 8, which is generated using entropy weights. Table 8 also shows the ranking comparison of EDAS, COPRAS, and SWEI with the entropy weighting method. Figure 4 provides a comparison of the ranking results. Alternative A-7 consistently achieved the 1st rank across all evaluation approaches. Alternatives A-4 secured the 2nd position, under all methods. Alternative A-1 was ranked in 3rd position by EDAS and COPRAS method, while it got 4th position by the SWEI method. Similarly, Alternative A-2 was ranked in 4th position by EDAS and COPRAS method, while it got 3rd position by the SWEI method. The alternative A-6 occupied the 5th position in all three methods. Similarly, Alternative A-5 was placed 6th by EDAS, COPRAS, and SWEI method under the entropy weighting method. Alternative A-8 was assigned the 7th position under the EDAS, COPRAS, and SWEI methods with entropy weights. Finally, alternative A-3 consistently received the last rank across all methods, regardless of the weighting strategy.

Alternatives	Appraisal scores by EDAS	Rank	Information scores by SWEI	Rank	Utility degree by COPRAS	Rank
A-1	0.685	3	8.218	4	87.55	3
A-2	0.623	4	8.189	3	86.44	4
A-3	0.087	8	8.359	8	65.19	8
A-4	0.911	2	8.114	2	97.44	2
A-5	0.383	6	8.296	6	76.37	6
A-6	0.448	5	8.247	5	78.69	5
A-7	0.947	1	8.106	1	100	1
A-8	0.167	7	8.341	7	66.99	7

Table 8: *Ranking comparison scores of the EDAS with other MCDM methods.*

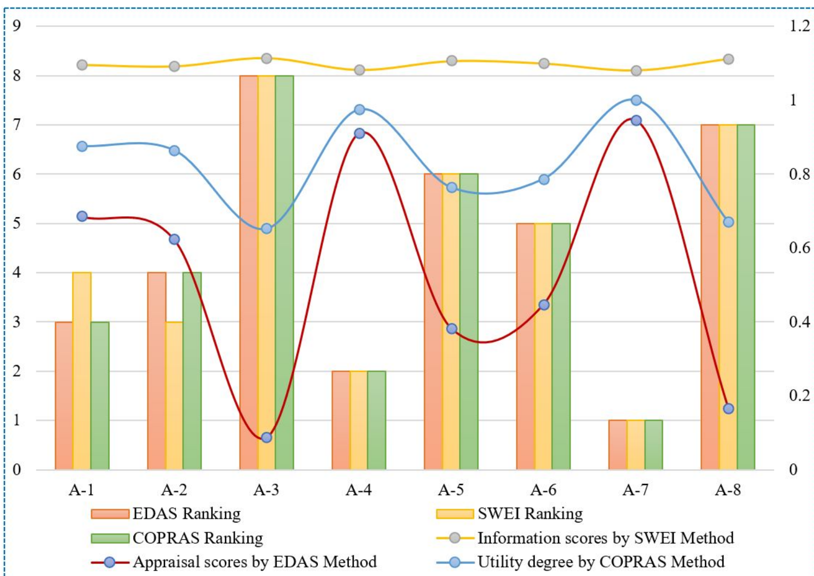

Figure 4: *Comparison of the ranking of the EDAS method with the SWEI and COPRAS methods.*

4.4. Sensitivity analysis

This subsection assesses the sensitivity of the ranking to variations in the input parameters or criteria weights. By systematically adjusting these values within a reasonable range and observing corresponding changes in the rankings, we can gain insights into the stability and robustness of the decision-making process. This analysis helps identify which criteria or parameters exert the most significant influence on the final rankings and how variations in these factors affect the relative positions of alternatives. Additionally, examining the impacts of different values allows us to understand the trade-offs inherent in the decision-making process and explore potential scenarios under varying conditions. By conducting this sensitivity analysis, decision-makers can better understand the implications of their choices and make more informed decisions that account for uncertainties and variations in input parameters. Table 9 shows the ranking by applying the equal weight for seven criteria ($1/7 = 0.143$) and entropy weight method. All individual rankings and the final ranking are the same. Nevertheless, a few slight ranking modifications compared to Table 8 can be observed. Figure 5 shows the ranking difference between the entropy weight and the equal weight method. As the weights changed, the ranking of A-7 and A-3 remained practically the same. So, the proposed EDAS method delivers the same results for decisions even with changed weighting scenarios, which is necessary for real-world use. It points out the factors that play the most important role in the end rankings. It allows those in charge to determine which factors are the most important and pay attention to these in future policy adjustments or assessments. Since there is little difference in the ranks between the two weight methods, it is clear that the approach stays consistent and flexible in various decision-making situations. The comparison between the entropy-based (objective) and equal (neutral) approaches proves that the method performs well in both precise and simple circumstances for decision-making.

Alternative	EDAS score by entropy weight	Ranking by entropy weight	EDAS score by equal weight	Ranking by equal weight
A1	0.685	3	0.71	3
A2	0.623	4	0.54	5
A3	0.087	8	0.12	8
A4	0.911	2	0.90	2
A5	0.383	6	0.54	4
A6	0.448	5	0.35	6
A7	0.947	1	0.97	1
A8	0.167	7	0.16	7

Table 9: *Sensitivity analysis by different weights for the FMS.*

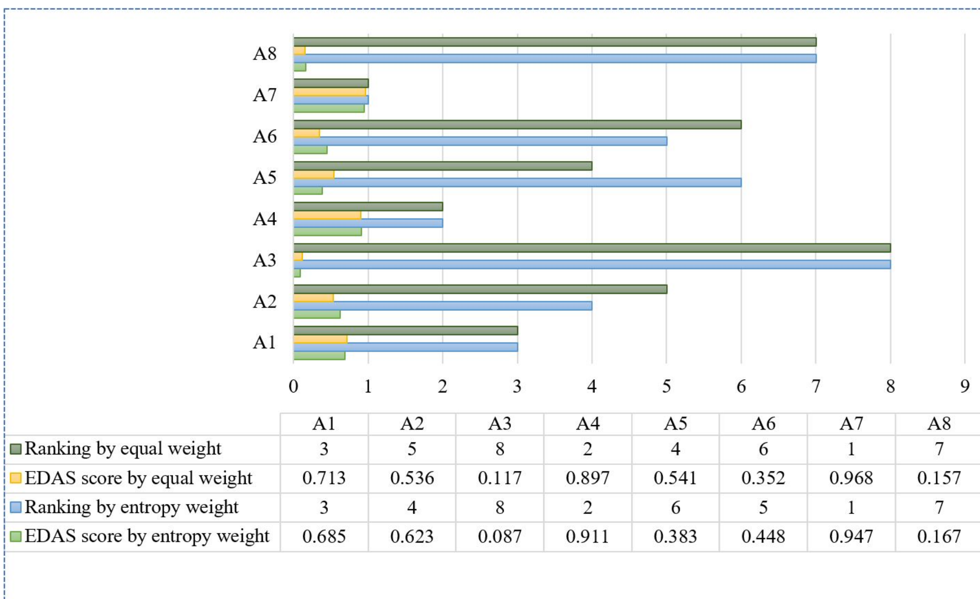

Figure 5: *Sensitivity analysis by different weights for the FMS.*

Worldwide manufacturing rivalry has compelled businesses to think about cutting costs while boosting quality and customization response. The development of FMSs promises enormous possibilities for enhancing flexibility and altering the competitive landscape by simultaneously guaranteeing cost-effectiveness and customized manufacture. Before investing in such innovative manufacturing methods that demands large capital outlays, one must take into account both the impacts that are easily quantified in dollars and those that are not. While precision-based approaches have been previously suggested to tackle the assessment and choice of flexible manufacturing technologies, these approaches are complex, knowledge-intensive, and may be beyond the reach of the individual decision-maker or user organization. A straightforward and rational scientific approach or mathematical instrument is required to assist user organizations in making an appropriate decision. This work proposes a methodology for choosing an appropriate FMS from a wide range of alternative FMSs. The methodology is based on a combinatorial mathematical approach combined with Shannon's entropy. When compared to other approaches that have been suggested in the past for choosing an FMS, this strategy is easier to put into practice. The FMSs selection characteristics function created in this work aids in the creation of the FMSs selection index, which assesses and ranks FMSs for a particular selection problem and may concurrently take into account any number of both quantitative and qualitative FMS selection attributes. In addition, the article proposes an entropy and EDAS conversion scale with ranked value judgments to express the qualitative FMS selection feature. The suggested technique is unique in that it provides a generic process that may be used for a variety of management science selection challenges that involve ambiguity and several both qualitative and quantitative selection qualities. Practical issues could come up when this kind of technique is put into practice. It is necessary to ascertain the values corresponding to the qualities of several possible FMS that the suggested technique would assess. These figures might occasionally be estimates. A what-if study, including many runs of the suggested model, can be necessary due to a lack of precise and trustworthy data. What-if analysis may benefit from further methodological advancements for more effective execution.

5. Conclusion

In this study, an evaluation of the FMS was undertaken with EDAS, and the objective weights were established through Shannon Entropy. With this method, alternatives for FMS could be systematically evaluated using data, making the decision-making process strong and dependable. A comparative review was made between the rankings and those produced by the COPRAS and SWEI methods to check their reliability. The analysis proved that both EDAS-Shannon Entropy, COPRAS, and SWEI rankings were consistent, which shows the methodology is solid and trustworthy. Moreover, a sensitivity analysis was done by adjusting the weights given to each criterion to see the ranking's consistency. The analysis showed that the rankings were mostly the same despite changes in the scenario, while only small shifts in some alternative positions were spotted. Such results demonstrate that the EDAS-Shannon Entropy method can provide reliable help for choosing FMS. The study offers helpful suggestions for people responsible for production and planning. The production systems are very important for producing the same types of products in the same quantity. Many manufacturing firms adopt flexible production systems to take advantage of the benefits provided by FMS. Many criteria are taken into account when selecting or evaluating any production system. Also, these criteria are sometimes confused with bias. Therefore, it is appropriate to use MCDM methods in FMS selection and evaluation. EDAS method ranks these systems according to the performance they show in the criteria of flexible production systems. The analysis of choosing FMS using the integrated EDAS and Entropy methods yields several key recommendations to improve decision-making and guarantee optimal results. The Entropy technique provides an impartial, data-driven approach to criterion weight assignment by examining the inherent variability (unpredictability) in the criteria. This ensures that more important factors receive proper attention, leading to more accurate and dependable results grounded in real data. Combining the Entropy method for objective weighting with the EDAS approach ensures a comprehensive and thorough evaluation of all FMS alternatives. This integrated method eliminates potential subjective biases and guarantees a well-rounded assessment of every option, thereby improving the selection process's accuracy. By following the above objective and comprehensive steps, organizations can make more informed, balanced decisions, ultimately leading to the selection of a more strategic and successful FMS. The integration of the Entropy and EDAS methods offers significant advantages for future research and applications across various fields, providing adaptable, versatile, and rigorous frameworks for addressing complex, multi-faceted problems. However, there are some limitations of the study. The suggested approach presupposes that the input data used is entire, consistent, and precise. Noisy and missing data could interfere with the integrity of the results in real-life industry settings. The application of Shannon Entropy will give only objective weights depending on data variability that might not fully represent the preferences of experts or priorities of managers in decisions in a practical situation. The methodology has been formulated in deterministic circumstances and makes no allowance for uncertainty or vagueness in the value of the criteria. This confines its use in the world where linguistic or imprecise data tends to prevail. Although the method is compared to COPRAS and SWEI to determine robustness, it would be worth greater validation on a wider scale by comparing the method against other hybrid or fuzzy MCDM approaches (e.g., TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), VIKOR, fuzzy EDAS). The framework takes a certain case of evaluation of FMS. Wider generalization might necessitate testing in several spheres or in an industrial environment of different complexity and set of requirements. Finally, Entropy weights are only based on the current data and thus fail to dynamically adjust to changing manufacturing situations or dynamic decision environments that could be factors in the flexible manufacturing context.

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