Enhancing Organizational Effectiveness through Job Evaluation in Manufacturing: A Scoring Method with Fuzzy ARAS Approach

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Abstract: - Job evaluation is a critical process for organizations to enhance organizational effectiveness by establishing fair and equitable compensation structures and aligning job roles with strategic goals. This study focuses on the manufacturing industry and aims to explore how job evaluation can be optimized through the integration of the fuzzy ARAS approach. By combining method, which assigns numerical scores to job factors, and factor analysis, which identifies underlying dimensions in a set of variables, this research proposes a comprehensive approach to job evaluation in manufacturing. This study contributes to the existing body of knowledge by offering a novel approach to job evaluation in the manufacturing industry. Research findings in practice can support HR professionals and organizational leaders in improving job evaluation practices, which can ultimately contribute to improved organizational performance and competitiveness in the manufacturing sector. Future research areas include investigating the extent to which the proposed approach is applicable in different manufacturing sub-sectors and assessing its long-term impact on organizational effectiveness.

Key Words: Job Evaluation, Fuzzy AHP, Organizational Performance, Human Resources, Fuzzy ARAS, Scoring, Effectiveness

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1 Introduction

In the job evaluation process, the processes of analyzing the skills and capacities of the employees and the work environment of the organizations in the production sector have been successfully handled and contributed to increasing organizational effectiveness. The job evaluation system in this study will enable the development of a fair remuneration policy in the relative evaluation of different job positions. In the manufacturing sector, it is very important to develop an effective job evaluation model due to the complexity of job roles, technical skills and specialization.

Model was developed by integrating the fuzzy ARAS method with the scoring method and the factor analysis approach. The selection of scoring method is through a scoring that numerically gives a importance factor to the skills, responsibilities and working conditions in job description phase of job modeling. Through factor analysis, which is conducting the dimensional delineation of the factors in the variable set, you are improving the precision of the job evaluation process comparing to just an overall job analysis. The purpose of this study is to build a useful fuzzy ARAS method and to interweave it with the scoring system of the job evaluation method using the factor analysis in the manufacturing sector. This study targets to generate an accomplishing model that could be useful in various kinds of human resource management sectors.

Job evaluation is an issue that is directly related to employee satisfaction in organizations and institutions. In this study, the fuzzy ARAS method is integrated with scoring and factor analysis to improve job evaluation processes and to define job roles more comprehensively. This study will assist HR managers and organizational leaders in the process of analysing the organizational performance of the manufacturing sector. This proposed approach can be easily applied to a wide range of sectors within the broad spectrum of the manufacturing sector. This study also enables the activation of organizational effectiveness.

The following sections of the study include the methodology used, the findings and analyses obtained and the literature review covering business evaluation processes through the integration of scoring method and factor analysis, the methodology in the next section, the case study in Section 4, and the conclusion and recommendations in the last section.

2 Literature Survey

Studies on the scoring method and factor analysis have been examined in order to make job descriptions and develop job and wage evaluation policies in the manufacturing sector and other business lines. According to the findings obtained from the literature, it is understood that scoring and factor analysis make significant contributions to increasing work productivity. This integrated structure was analyzed by using scoring and factor analysis methods together with the fuzzy ARAS method. In this study, a comprehensive application about the structure of the proposed model is given in the light of the findings obtained from the literature. In particular, it is seen that these two methods, scoring and factor analysis methods, have not been considered together with MCDM methods and there is a gap in the literature.

In their investigation, Kaur and Kanoge examined organizational performance research and position evaluation practices in manufacturing organizations (Kaur and Kanoge, 2021). They studied the evaluation of task processes by involving factors analysis and scoring tools. Nazarian and co-authors in their study came up with the integrated model (in the service system sector) [2]. Eventually, organizational policy regulation and business operations efficiency rose at the end of study by explaining this fact. Another example is eco-gardening as it is the best situation to provide employees with healthcare facilities while keeping them mentally healthy [3]. Organizational structure and effectiveness have been widely studied with numerous researches on the subject (Factor Analysis [4], [5], [6], [7] and [8]).

Behera et al. considered a manufacturing firm as their area of study according to [8]. The phase of Nadiri and Tanova (2010) [10] used analysis technique tools (scoring values & factor analysis) to strengthen the organizational effectiveness in the manufacturing sector. In this study, they evaluated the correlation between work force effectiveness, participation of the employees in the planning and realization of the company targets and customer satisfaction with the outcome of the job evaluation [11], [12]. The researchers use different models and techniques of scoring and factor analysis [11[, [12], [13], [14], [15], [16], [17]] to study the several applications of these methods in the manufacturing sector.

Besides determines the efficiency of the comprehensive methods employed with the technique both the rating and factor analysis in enhancement organizational performance in the manufacturing sector. Job evaluation is not only concerned with the technical aspects of organizational performance but also links with the people management factors, like performance management, talent management, employee satisfaction and strategic decision. These studies always add the subject to the development of its philosophy and understanding by examining the losses and incomes that can be identified or accrued in the sector of manufacturing if the integrated approaches are practiced.

The reliant outputs provide the insight of the fact that job evaluation in the manufacturing sector mapping the employee effectiveness using scoring method and the factor approach makes a lot of sense. They critically analyze certain elements of job evaluation that has great implications on the firms operation, including performance assessment, talent development, employee satisfaction and strategic decision. It is interesting to note that these studies provide useful information on the advantages and drawbacks of employing the integrated system within the framework of job evaluation in manufacturing industries.

3 The ARAS Approach for Fuzzy Factor Analysis

The particular area of consideration of fuzzy set theory is the construction of mathematical instruments which can provide for the expression, the modelling and the analysis of the many uncertainties that might affect the decision-making process. It could become ambiguous for readers to know the analysis of the information, so also verbal clarifiers might be needed. The concept of linguistic variables allows qualitative or subjective information to be expressed quantitatively.

Linguistic variables allow analysis and performance values to be obtained with the graded evaluation structure of each criterion in the decision-making process [18], [19], [20], [221], [22], [23], [24], [25]. Decision makers can express their subjective judgments in a simpler way by using linguistic variables. In short, fuzzy set theory and linguistic variables can effectively evaluate subjective uncertainty in decision-making processes and contribute to big data analysis in the same direction. Fuzzy numbers, uncertainties in number values, can be expressed by the concept of fuzzy set. Here $A = \{x \in R | \mu_A(x)\}$, x represents the values on the real line R (-∞<x<+∞) and is a continuous mapping from R to the closed interval [0,1].

The membership function $\mu_{\tilde{A}}(x)$ assigns a degree of membership to each value x, indicating its membership in the fuzzy number A.

Triangular fuzzy numbers are preferred over trapezoidal fuzzy numbers in many applications, as they are easier to calculate and possess useful features for decision-making. A triangular fuzzy number, denoted as $\tilde{A} = (l, m, u)$, where l≤m≤u, is characterized by its triangular membership function. The membership function $\mu_{\tilde{A}}(x)$ of a triangular fuzzy number is defined as follows:

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l \text{ or } x > u \\ (x-l)/(m-l), & l \le x \le m \\ (x-u)/(m-u), & m \le x \le u \end{cases} \tag{1}$$

The automatic evaluation process uses various linguistic variables which are then converted into fuzzy numbers and following, the properly weighting values are obtained. In other turn, ARAS-F and the weight values produced by FAHP will preset to evaluate firmly the criteria and rank them up. By this means, a good analyzer can correlate between these two parameters, quantitative and qualitative, and produce even more accurate data. To estimate the degree of membership of the data, trapezoidal fuzzy number is defining, where the numbers l, m and u are just the triangular fuzzy numbers, i.e. l≤m≤u. Now for the values different from [l, u] the membership value is zero, as well. Fuzzy numbers, that are used to relate linguistic values with numerical one's, can also be used to analyze linguistic values [26], [27], [28].

$$\forall \alpha \in (0,1)\ \tilde{A}_\alpha = [l^\alpha, u^\alpha] = [(m-l)\alpha + l, -(u-m)\alpha + u] \tag{2}$$

The method combines classic Analytical Hierarchy Process (AHP) with instants of linguistic and fuzzy values. Through applying linguistic variables as well as fuzzy numbers the opinions of the assessors are factored in better than in the classic approach where even the most subjective evaluations were made on a purely numerical scale. The methodology used in the research is based on FAHP approach which offers decision makers a variety of ways to say linguistically what matters to them and add a linguistic variables to the evaluation process.

3.1 Employing Fuzzy Analytical Hierarchy Process (FAHP) to ascertain criteria weights

AHP was first introduced by Saathy in 1980 and from this basic nature a tool conceived for assessing the relative weight of criteria in MCDM. In classical AHP a nine-point scale is used is applied instead of different scales to the fixed items to compare their relative novelty but in this process one disregards the fact that there exists useless uncertainty and subjectivity which humanizes comparison. To withstand this uncertainty FAHP was used.

For this example a 9 point scale was used, where $(\tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9})$ indicate different strength, priority, or importance of each pair of items. Fuzzy numbers are linked to a membership function that expresses the degree of membership of each value. Fuzzy numbers are combined with linguistic variables and express the uncertainty in the pairwise comparison. With this approach, triangular fuzzy numbers provide probability values that are not single-point but interval values, making the subjective judgment of decision makers more realistic(in Table 1).

Table 1. Definition and membership function of fuzzy scale

Intensity of importance	Fuzzy number	Definition	Membership function
1	$\tilde{1}$	Equal importance (EI)	(1, 1, 2)
3	$\tilde{3}$	Moderate importance (MI)	(2, 3, 4)
5	$\tilde{5}$	Strong importance (SI)	(4, 5, 6)
7	$\tilde{7}$	Very strong importance (VSI)	(6, 7, 8)
9	$\tilde{9}$	Extremely more importance (EMI)	(8, 9, 10)

Using the fuzzy comparison matrix, the FAHP method can derive the weights of the evaluation criteria, taking into account linguistic variables and subjective judgments expressed in triangular fuzzy numbers. These weights provide insight into the relative importance or significance of each criterion in the decision-making process.

The steps of the FAHP method used in this study are:

1. Comparison of performance scores: The pairwise comparison values are expressed in linguistic variables using triangular fuzzy numbers.

2. Fuzzy comparison matrix: The fuzzy evaluation matrix is expressed in terms of triangular fuzzy numbers and their relative equivalents are obtained.

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & 1 \end{bmatrix} \tag{3}$$

3. Fuzzy eigenvalue solution: The fuzzy eigenvalue $\tilde{\lambda}$ is a nonzero nx1 fuzzy vector of the number x in the fuzzy decision matrix and it contains the largest value of λ̃_max. It aims to find the value of x with the unit matrix of appropriate dimensions I using equations (4) and (5).

$$\tilde{A}\tilde{x} - \tilde{\lambda}\tilde{x} = 0 \tag{4}$$

$$(\tilde{A} - \tilde{\lambda} I)\, \tilde{x} = 0 \tag{5}$$

Equations (4), (5) and (6), α-cutting techniques are used in the solution process of the fuzzy decision matrix, taking into account the fuzzy λ̃_max eigenvalue and n×1 fuzzy vector.

$$\det(\tilde{A} - \tilde{\lambda} I) = 0 \tag{6}$$

The characteristic equation is a polynomial equation in $\tilde{A}$, and solving it yields the fuzzy eigenvalue $\tilde{\lambda}$. Substituting the obtained $\tilde{\lambda}$ back into the equation ($\tilde{A}$ - $\tilde{\lambda}$I) x̃ = 0 allows us to determine the corresponding fuzzy eigenvector x̃.

$$[a_{11l}^{\alpha} x_{1l}^{\alpha}, a_{11u}^{\alpha} x_{1u}^{\alpha}] \oplus \cdots \oplus [a_{inl}^{\alpha} x_{nl}^{\alpha}, a_{inu}^{\alpha} x_{nu}^{\alpha}] = [\lambda x_{il}^{\alpha}, \lambda x_{iu}^{\alpha}] \tag{7}$$

where,

$$\tilde{A} = [\tilde{a}_{ij}], \tilde{x}^{t} = (\tilde{x}_1, \ldots, \tilde{x}_n), \tag{8}$$

$$\tilde{a}_{ij}^{\alpha} = [a_{ijl}^{\alpha}, a_{iju}^{\alpha}], \tilde{x}_i^{\alpha} = [x_{il}^{\alpha}, x_{iu}^{\alpha}], \tilde{\lambda}^{\alpha} = [\lambda_l^{\alpha}, \lambda_u^{\alpha}] \tag{9}$$

for $0 < \alpha \leq 1$ and all i, j, where $i = 1,2,\cdots,n; j = 1,2,\cdots,n$.

By adjusting the value of α, the decision maker(s) can express their level of optimism or pessimism in their preferences. A larger value of α indicates a higher degree of optimism, while a smaller value of α reflects a higher degree of pessimism.

The optimism index, denoted by μ, expresses the degree of confidence and satisfaction of decision makers with fuzzy judgments. The optimism index is calculated by the following formula:

μ = α · μ_max + (1 - α) · μ_min (10)

where α is the weight value assigned to the maximum value of μ and (1 - α) is the weight value assigned to the minimum value of μ.

The degree of membership μ provides information on the level of trust and satisfaction of decision makers and thus helps in understanding subjective preferences and decision making.

$$\tilde{a}_{ij}^{\alpha} = \mu a_{iju}^{\alpha} + (1 - \mu) a_{ijl}^{\alpha}, \quad \forall \mu \in [0, 1] \tag{11}$$

After fixing the degree of membership, i.e. the optimism index μ and the constant value α:

1. The max () and min () values are calculated for each element in the fuzzy judgment matrix.

2. The optimism index μ is adjusted and the formula is calculated:

μ = α - max( ) + (1 - α) - min( ) (12)

3. Each value in the fuzzy judgment matrix is compared with μ and takes the value 1 if the comparison value is greater than μ and 0 if it is less than or equal to μ.This process results in a binary matrix where the elements are either 1 or 0, depending on whether they meet the threshold of the index of optimism μ.

This matrix represents the degree of satisfaction or preference for each element in the fuzzy judgment matrix, based on the fixed value of α.

Note that the value of α determines the balance between optimism and pessimism in the decision maker's preferences. By adjusting α, different levels of optimism can be incorporated into the analysis.

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12}^{\alpha} & \cdots & \tilde{a}_{1n}^{\alpha} \\ \tilde{a}_{21}^{\alpha} & 1 & \cdots & \tilde{a}_{2n}^{\alpha} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{a}_{n1}^{\alpha} & \tilde{a}_{n2}^{\alpha} & \cdots & 1 \end{bmatrix} \tag{13}$$

The eigenvector is calculated by fixing the value of μ and determining the maximum eigenvalue.

(4) Consistency ratio. To ensure the accuracy of comparative weights, the value of the consistency ratio CR must be less than 0.10.

$$CR = CI/RI, \text{where } CI = (\lambda_{\max} - n)/(n-1) \quad (14)$$

(5) Aggregation of priorities. In the last step, the local priorities at different levels in the decision hierarchy are aggregated to derive the criteria decisions. In the aggregation process, geometric mean or weighted mean approaches are preferred. The procedures used to determine the priorities, i.e. weight values, are as follows:

1. Using FAHP, the local priorities to be included in the decision matrix are determined.

2. Local priorities are taken into account to obtain aggregate weights. If local priorities are denoted by P1, P2 and P3, their weights will be W1, W2 and W3 respectively, and the combined global priority is

Composite Global Priority = W1 * P1 + W2 * P2 + W3 * P3 (15).

3. Global priorities are normalized so that the sums are equal to 1.

$$CR = CI/RI, \text{where } CI = (\lambda_{\max} - n)/(n-1) \quad (16)$$

With these steps, global priority values are determined and the weight value obtained is used in the next analysis process.

3.2 Utilizing the Fuzzy ARAS

The ARAS-F (Contribution Rate Assessment - Fuzzy) method analyzes and ranks performance by comparing it with the ideal alternative assessment method and the following steps are used:

Step 1: Define the ideal alternative: The ideal alternative is determined based on the maximum value for benefit criteria (set B) and the minimum value for cost criteria (set C). The ideal alternative is represented as:

$$\tilde{x}_{0j} = \max_i c_{ij}, \forall j \in B;\ \tilde{x}_{0j} = \min_i c_{ij}, \forall j \in C \quad (17)$$

Step 2: Normalize the values: Normalize the values in the decision matrix using the following equations:

$$\bar{d}_{ij} = \tilde{d}_{ij} \Big/ \sum_{i=0}^{m} \tilde{d}_{ij}, \forall j \in B;\quad \bar{d}_{ij} = (1/\tilde{d}_{ij}) \Big/ \sum_{i=0}^{m} (1/\tilde{d}_{ij}), \forall j \in C \quad (18)$$

Step 3: Construct the weighted-normalized matrix: Multiply the normalized values by the significance coefficients:

$$\hat{\tilde{d}}_{ij} = \tilde{d}_{ij} \times \tilde{w}_j,\ \forall j, i \quad (19)$$

Step 4: Compute the overall utility: Calculate the overall utility of each alternative by summing the weighted-normalized values for each alternative:

$$\tilde{S}_i = \sum_{j=1}^{n} \hat{\tilde{d}}_{ij},\ \forall i \quad (20)$$

Step 5: Defuzzify the overall utility: Apply the Center of Area (COA) method to defuzzify the fuzzy number S̃i and obtain a crisp value:

$$S_i = (s_{i1} + s_{i2} + s_{i3})/3, \quad \forall i \quad (21)$$

Step 6: Calculate the relative utility: Compute the relative utility (Ki) of each alternative by dividing its defuzzified overall utility by the overall utility of the ideal alternative:

$$K_i = S_i/S_0, \forall i \quad (22)$$

Step 7: The alternatives are ranked relatively and the best alternative is represented by the K_i value.

With these steps, the criteria in the fuzzy ARAS method are evaluated according to their performance and the ranking process is carried out from the best performance to the worst performance.

4 Application

The integrated use of the scoring method and factor analysis in the analysis process will contribute to increasing organizational efficiency. Objective and consistent job evaluations of organizations, analyzing job roles with objective rules and reducing prejudices will also increase internal reliability. With fair compensation structures, employees' motivation and trust within the organization will also increase. With a unified approach, job roles are also aligned with strategic goals, resulting in a more efficient structure.

Table 1 Criterias and Main Performance Scales

Critera	Recruitment & Selection	Workforce planning	Training & Development	Compensation & Benefits	Health & Safety	Performance Appraisal	Job Evaluation
Task complexity	3	7	9	7	7	7	9
Task relevance	5	7	9	7	7	5	7
Professional knowledge	9	7	5	7	3	5	7
Knowledge updates	7	5	7	7	5	3	9
Physical skills	3	5	9	9	7	5	3
Experience	7	7	5	7	5	7	5
Responsibilities for financial resources	5	5	7	9	3	9	5
Responsibilities for human resources	7	3	5	3	5	5	3
Mental effort	7	5	9	5	3	3	7
Physical effort	7	7	5	3	5	7	9
Working conditions	9	7	5	5	3	5	3
Planning and organizational skills	5	7	9	7	5	7	5
Communication and relationship skills	7	7	7	5	3	5	7
Analytical and judgemental skills	7	5	7	5	3	3	9
Innovation skills	9	7	5	3	5	7	3

Task Characteristics	Knowledge	Responsibility	Effort/Environment	Skills

Table 1 shows the basic performance scales and score grades of the criteria. The criteria were analyzed under 5 sub-headings. These titles are task characteristics, knowledge, responsibility, Effort/Environment and Skills. In this application, the factors and sub-factors used are as follows (in Table 1):

- Task Characteristics: 1.1 Task Complexity 1.2 Task Relevance
- Knowledge: 2.1 Professional Knowledge 2.2Knowledge Updates 2.3 Physical Skills 2.4 Experiences
- Responsibility 3.1 Responsibility for Financial Resources 3.2 Responsibilities for Human Resources
- Effort/Environment 4.1 Mental Effort 4.2 Physical Effort 4.3 Working Conditions Skills 5.1 Planning and Organizational Skills 5.2 Communication and Relationship Skills 5.3 Analytical and Judgemental Skills 5.4 Innovation Skills

This ensures that job roles designed and evaluated in a manner that supports the organization's objectives and maximizes productivity and efficiency.

These factors and sub-factors used to evaluate and assess various aspects related to workforce management. Each factor represents a specific area or attribute that considered important in the decision-making process. For example, the Task Group includes factors such as task complexity, task relevance, skill, and initiative and improvement, which are essential for assessing an individual's competency and expertise. Similarly, the Responsibility Group focuses on factors related to different types of responsibilities, such as financial resources responsibility, and human resources responsibility.

A general overview of the calculation procedure includes the determining the weights of evaluation criteria in fuzzy AHP.

1. Construct the pairwise comparison matrix: Experts or decision-makers compare the importance of each criterion with respect to the others using linguistic terms. The comparisons recorded in a pairwise comparison matrix, where each element

3. α-cut fuzzy comparison matrix: The fuzzy comparison matrix is obtained by applying α-cuts to the fuzzy numbers in the binary comparison matrix. The α-cut also expresses the degree of confidence. It is an auxiliary factor used in the analysis of uncertainty.

4. Fuzzy eigenvalue analysis: It is used to determine the weights of the evaluation criteria. In the equation $\tilde{A}\tilde{x} = \tilde{\lambda}\tilde{x}$, where $\tilde{A}$ is the α-cut fuzzy comparison matrix, $\tilde{x}$ is the eigenvector, i.e. the relative weight of each criterion, and $\tilde{\lambda}$ is the eigenvalue.

5. Consistency ratio: Consistency ratio (CR) analyzes how pairwise comparisons compare with the random consistency index (RI).A lower CR value indicates better consistency. If the CR exceeds a predefined threshold (typically 0.10), the judgments may need to be revised.

6. Aggregate the weights: The local weights obtained for each criterion at different levels of the decision hierarchy aggregated to determine the composite global weights. This aggregation process combines the relative importance of criteria from different levels to obtain a comprehensive weight for each criterion. The criteria were evaluated by 5 experts and the averages of the evaluation results are shown in Table 2.

Table 2 Pairwise Comparison Matrix values of criteria with linguistic expressions

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
C1	-	MI	SI	MI	EI	MI	EI	EI	EI	SI	VSI	EMI	VSI	MI	EI
C2		-	MI	EI	MI	MI	SI	EI	EI	SI	MI	SI	VSI	MI	EI
C3			-	EI	MI	EI	EI	MI	EI	MI	EI	EI	MI	EI	SI
C4				-	EI	EI	MI	EI	EI	MI	EI	EI	EI	MI	EI
C5					-	MI	SI	EI	EI	MI	EI	MI	EI	EI	MI
C6						-	MI	EI	MI	MI	EI	MI	MI	EI	SI
C7							-	SI	VSI	SI	SI	VSI	MI	EI	VSI
C8								-	EI	EI	EI	EI	MI	EI	EI
C9									-	SI	VSI	SI	SI	VSI	SI
C10										-	EI	MI	EI	EI	MI
C11											-	SI	EI	MI	EI
C12												-	MI	SI	VSI
C13													-	EI	MI
C14														-	SI
C15															-

The weightage of the sub-criteria can be established by pursuing the steps delow. The particular numeric values and strategies may change according to the chosen fuzzy directive and the informationstated in Table 3. The average rating values obtained by analogous evaluation of all criteria were set fuzzily as well. While the variety of the assessment results on one hand occupy a part of the Table 3, on the other hand, the pairwise comparison matrix appear at this point. Even though the answer sheet is the hidden word as Table 4, then the score of the criteria is uncovered in Table 5.

Table 3 Pairwise comparison matrix

[illegible]

According to the results of this ranking, the criteria with the highest importance are C1- "Task complexity", C2-"Task relevance", C7-"Responsibilities for financial resources", C9-"Mental Effort. The lowest value is C13-"Communication and judgmental skills", C10-"Physical Effort", C15-"Innovation Skills". In Table 5, the weights of criteria within the different levels of the evaluation matrices, as well as the importance ranking for the parameters are presented (in Table 6).

Table 4 Weight values

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
Weight	0.142	0.114	0.088	0.060	0.072	0.068	0.109	0.050	0.096	0.029	0.045	0.046	0.028	0.056	0.034

Table 5 Ranking weight values

[illegible]

These results provide insight into the relative importance of different criteria in the evaluation of parameters. The weights obtained through FAHP help prioritize these factors and guide the decision-making process in selecting and ranking the parameters according to their performance.

Table 6 Normalized values.

[illegible]

In the evaluation and ranking of the human resources evaluation alternatives using the ARAS-F method, the following steps were followed:

Step 1: Data collection and linguistic conversion: The experts' opinions and evaluations were collected and converted into triangular fuzzy numbers to represent the linguistic values. This conversion allows for handling subjective uncertainty in the decision-making process.

Step 2: Construction of the fuzzy decision-making matrix: Using the global weights of all sub-criteria obtained from the FAHP, a fuzzy decision-making matrix was constructed. This matrix incorporates the performance evaluations of the parameters alternatives based on the collected data.

Step 3: Calculation of performance indices: The ARAS-F method applied to calculate the performance indices of the parameters alternatives using the fuzzy decision-making matrix. This step involved the normalization and weighting of the performance values according to the ARAS-F procedure described earlier.

Step 4: Evaluation and ranking of alternatives: As a result of the evaluation using the Fuzzy ARAS method, workforce planning was the most important criterion, followed by job evaluation as the second most important criterion. Recruitment and selection ranked 3rd, workforce planning ranked 4th and this criterion was followed by compensation and benefits, Performance Appraisal and lastly health & safety.

Table 7. Final performance indices of human resources with respect to fuzzy MCDM methods

Human Resource Evaluation Parameters	$\tilde{S}_i$	S_i	K_i	Ranking
Recruitment and Selection	[illegible]	0,426333333	0,666667	3
Workforce Planning	[illegible]	0,397133333	0,47168	4
Training & Development	[illegible]	0,476200000	1	1
Compensation & Benefits	[illegible]	0,377133333	0,33776	5
Health & Safety	[illegible]	0,326600000	0	7
Performance Appraisal	[illegible]	0,372333333	[illegible]	6
Job Evaluation	[illegible]	0,427533333	[illegible]	2

6 Conclusion

In this study, fuzzy ARAS (Additive Ratio Assessment) technique is developed and proposed together with an integrated scoring structure to increase organizational efficiency and effective job evaluation in the manufacturing sector. Relatively focusing on the process of defining and scoring processes, business processes were analysed. This study is expected to contribute to human resources applications, especially in job evaluation, compensation management and performance analysis. The limitations and deficiencies in traditional job evaluation methods have been addressed in this study and a new perspective has been brought to this subject. With the scoring system integrated with the fuzzy ARAS technique, the evaluation criteria and the relationships between them were also analysed. The study also examined the ambiguities between job evaluation and job appraisal and the effects of these ambiguities on the system. The subjective judgments of the experts and their evaluations using linguistic variables were included.

The findings of the study show the applicability of this study in this field. The use of a fuzzy ARAS approach with more than one evaluation criterion allows the job evaluation process to be evaluated with a more robust and reliable analysis.

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