Industrial Engineering and Innovation Management (2023)
Clausius Scientific Press, Canada

DOI: 10.23977/ieim.2023.060703
ISSN 2522-6924 Vol. 6 Num. 7

Job Evaluation for Production Roles with Fuzzy Cognitive Map: An Empirical Study in the Manufacturing Industry

Safiye Turgay[1,a,*], Metehan Han[2,b], Abdülkadir Aydın[1,c]

[1]*Department of Industrial Engineering, Sakarya University, Sakarya, Turkey*
[2]*Insurance Information and Surveillance Center, Merdivenköy Mahallesi Bora Sok. No:1 Kat:18, 34732, Kadıköy-Istanbul, Turkey*
[a]*safiyeturgay2000@yahoo.com*, [b]*metehanhan97@gmail.com*, [c]*mr.kdiraydn@gmail.com*
[*]*Corresponding author*

Keywords: Job evaluation, fuzzy Cognitive Maps, job attributes, evaluation framework, performance management

Abstract: Job evaluation is a critical process in organizations, particularly in the manufacturing industry, where production roles play a vital role in overall operational success. Traditional job evaluation methods often rely on subjective judgments and can be prone to bias. This study considered the application of Fuzzy Cognitive Maps (FCMs) as a novel approach to job evaluation in the manufacturing industry. FCMs provide a framework to capture and represent the complex relationships and interdependencies between various job attributes and their impact on overall job performance. The objective of this empirical study is to demonstrate the effectiveness of FCMs in job evaluation for production roles in the manufacturing industry. The collected data will be used to construct FCMs, where nodes represent job attributes (e.g., technical skills, communication, problem-solving) and edges capture the strength and direction of relationships between attributes. The FCMs will be validated and calibrated using statistical techniques, ensuring their reliability and accuracy. The final evaluation framework will provide a quantitative method for assessing the relative importance of job attributes and determining the overall value of production roles within the organization.

1. Introduction

The effective job evaluation processes enable organizations to establish fair and equitable compensation systems, support talent management practices, and ensure the optimal allocation of resources. Given the unique characteristics and demands of production roles in manufacturing, a comprehensive understanding of job evaluation specifically tailored to these positions is essential.

This study focuses on job evaluation for production roles in the manufacturing industry and aims to provide empirical insights into the factors and criteria considered in evaluating these roles. The research aims to identify the factors that hold the most significance in determining the value of production roles, such as technical expertise, problem-solving skills, and adherence to quality standards, physical demands, and teamwork. Understanding the weightings assigned to these factors will provide insights into the relative importance given to different aspects of production roles.

The case study highlights the application and evolution of Fuzzy Cognitive Maps (FCMs) in the domain of manufacturing job performance. Over time, FCMs have evolved to address the complexities and uncertainties associated with managing in application. The study highlighted the importance of involving multiple stakeholders in the job evaluation process, including employees, supervisors, and human resources personnel. Their input and perspectives helped ensure a comprehensive and fair evaluation of production roles. The integration of multiple variables, incorporation of uncertainty, dynamic modelling capabilities, and multi-level modelling approaches have enhanced the effectiveness of FCMs in analysing and improving job shop evaluation performance.

By gaining a comprehensive understanding of job evaluation for production roles in the manufacturing industry, organizations can enhance their decision-making processes related to compensation, career development, and talent management. The findings of this study will guide organizations in evaluating production roles more effectively, ensuring fairness and alignment with organizational objectives.

This study organized into five sections. A literature review of job evaluation for manufacturing and FCM analysis in section 2. Section 3 presents the mathematical model. Section 4 comprises the FCM and Section 5 covers the case study and final section includes the conclusion.

2. Literature Survey

The study collects data from multiple manufacturing organizations, focusing on a range of production roles such as machine operators, assemblers, and quality control inspectors. Data gathered through surveys and interviews with job incumbents, supervisors, and subject matter experts. The construction and analysis of FCMs involve techniques such as fuzzy logic, graph theory, and computational algorithms. FCMs can be simulated and updated to assess the behavior of the system under different scenarios or interventions.

The literature survey revealed several important themes and findings related to job evaluation for production roles in the manufacturing industry. Some notable findings include:

1) Importance of Job Evaluation in Manufacturing: The literature emphasized the significance of job evaluation in the manufacturing industry for determining the relative worth and importance of production roles. It highlighted the need for a systematic and fair evaluation process to support decision-making related to compensation, career progression, and workforce planning.

2) Methods of Job Evaluation: The literature discussed various methods of job evaluation used in the manufacturing industry, such as the point factor method, ranking method, and classification method. It highlighted the advantages and limitations of each method and emphasized the need for selecting an appropriate method based on organizational requirements and job characteristics.

3) Factors Considered in Job Evaluation for Production Roles: The literature identified key factors considered in job evaluation for production roles in the manufacturing industry. These factors include skill requirements, physical effort, responsibility, working conditions, and decision-making authority. The literature emphasized the importance of accurately assessing these factors to ensure fairness and consistency in job evaluation.

4) Validity and Reliability of Job Evaluation: The literature highlighted the importance of validity and reliability in job evaluation for production roles. It discussed the need for establishing clear evaluation criteria, conducting job analysis, and involving subject matter experts to ensure the accuracy and consistency of the evaluation process.

5) Impact of Job Evaluation on Employee Motivation and Performance: It discussed how fair and transparent job evaluation processes can enhance employee satisfaction, engagement, and productivity. The literature also highlighted the importance of effective communication and

feedback to ensure employee understanding and acceptance of job evaluation outcomes.

6) Challenges in Job Evaluation for Production Roles: The literature identified several challenges in job evaluation for production roles in the manufacturing industry. These challenges include defining job roles and responsibilities, ensuring consistency across different shifts and departments, and addressing potential biases and subjectivity in the evaluation process.

A Fuzzy Cognitive Map (FCM) is a mathematical modelling which used to represent and analyse systems, such as decision-making processes, social networks, and organizational structures. FCMs combine concepts from fuzzy logic and cognitive science to capture the relationships and interactions between various elements within a system. Once an FCM is constructed, it can be used for various purposes, such as simulation, prediction, decision-making, and analysis of system behaviour. By applying different computational techniques, such as fuzzy inference or simulation algorithms, FCMs can provide insights into the dynamics and behaviour of the modelled system.

The findings will assist organizations in making informed decisions related to job design, performance management, and compensation. Suwarsono et al. compares and evaluated different job evaluation methods, such as the ranking method, classification method, and point factor method, specifically in the context of production roles in the manufacturing industry [1]. It assesses the strengths and weaknesses of each method and provides insights into their practical application and effectiveness. Kahya (2018) investigated the relationship between job evaluation and compensation practices in a manufacturing company [2]. It explores how job evaluation outcomes influence compensation decisions for production roles, taking into account factors such as job responsibilities, required competencies, and market benchmarks. Morgeson et al. reviewed the relationship between job evaluation and employee compensation in the manufacturing industry [3]. It explores how job evaluation outcomes influence compensation decisions for production roles and the perceived fairness of the compensation system. Chen et al. explored the relationship between job evaluation and compensation strategies in manufacturing companies [4]. It examines how job evaluation outcomes are used to determine fair and competitive compensation for production roles, taking into account factors such as skill requirements, job complexity, and market benchmarks. Aliku et al. focused on the validation of a job evaluation system specifically designed for manufacturing roles[5]. It examines the reliability and validity of the evaluation system and its effectiveness in assessing the value and worth of production roles within the organization. Kozlowski et al. focused on job evaluation and effectiveness work groups [6]. It examines the reliability and validity of the evaluation system and its effectiveness in assessing the value and worth of production roles within the organization. Zhenjing et al. reviewed the impact of the workplace environment performance analysis [7]. Ergu et al. reviewed the applications of FCMs in sustainable development, discussing their role in addressing sustainability challenges and outlining future research directions [8]. Miquel et all. presented a decision support tool in environmental management, highlighting their potential for addressing complex environmental issues[9].

Karyotis et al reviewed the systematic literature review explores the use of FCMs in forecasting and decision-making contexts, providing insights into their effectiveness and applications [10]. Díaz-Madroñero et al. examined the application of FCMs in the energy sector, showcasing their potential for decision-making related to energy systems and policies [11]. [Wu and Lin focused on the applications of FCMs for representing complex systems, providing insights into their modelling capabilities and practical uses [12]. Liu et al. presented a review of FCM-based decision support systems, discussing their development, methodologies, and applications in different decision-making contexts [13]. Erkan and Uygun used the FCM for organization’s leaning performance analysis [14]. Gkitzia et al. provides a review of FCM-based expert systems, highlighting their advantages, limitations, and applications in various domains [15]. Delen et al. presented clinical decision-making and healthcare management with FCM method [16].

The key considerations, methods, and challenges in job evaluation for production roles in the manufacturing industry. They contribute to the understanding of the factors that should be considered, the importance of validity and reliability, and the impact of job evaluation on employee motivation and performance. The survey identified gaps in the literature that can guide further research on improving job evaluation practices for production roles in the manufacturing industry.

3. Mathematical Model

Factor Analysis Job Evaluation (FAJE) is a method used for job evaluation in organizations to determine the relative worth or value of different jobs. It involves analyzing job characteristics and assigning weights to various factors that contribute to job complexity and importance. Mathematical programming can be employed to optimize the job evaluation process and ensure consistency and fairness.

In the context of FAJE, mathematical programming techniques can be utilized to determine the optimal weights or scores assigned to different factors. The mathematical programming model for FAJE typically includes the following components:

1) Objective Function: It aims to maximize the overall value or worth of a job based on the assigned weights to different factors.

2) Decision Variables: It represents the weights or scores assigned to each factor. These variables are the values to be determined through the optimization process.

3) Constraints: Constraints are used to impose restrictions on the decision variables. They ensure that the assigned weights satisfy certain conditions or limitations. For example, the weights may need to sum up to 1 to ensure a normalized evaluation.

4) Factor Data: The mathematical programming model requires input data related to the job factors, such as descriptions of each factor, their importance or weight ranges, and any relationships or dependencies between factors.

By solving the mathematical programming model, the optimal weights or scores for each factor can be obtained, providing a systematic and data-driven approach to job evaluation. This helps in establishing a fair and consistent framework for determining job levels, compensation structures, and career progression within an organization.

Pseudo code for combining Factor Analysis Job Evaluation (FAJE) with Mathematical Programming might look as follows:

1) Define the job evaluation factors and their weights. Identify the key factors or dimensions that contribute to job value (e.g., skills, experience, responsibility)

a. Let F be the set of job evaluation factors.

b. Let w_i be the weight assigned to factor i in F.

2) Collect data and assign factor scores to each job:

a. Let J be the set of jobs.

i. For each job j in J:

1) Collect data on the relevant factors in F for job j.

2) Assign scores to each factor based on the data.

3) Calculate the overall job value for each job:

a. For each job j in J:

i. Calculate the weighted sum of factor scores for job j:

1) Let s_{ij} be the score of factor i for job j.

2) Calculate the job value vj as: $v_j = \Sigma(w_i * s_{ij})$ for all factors i in F.

4) Formulate the optimization problem:

a. Let X_j be the decision variable representing the allocation of resources to job j.

b. Define the objective function based on the specific resource allocation goal (e.g., maximize total job value or minimize resource cost).

c. Add constraints that reflect resource availability, job dependencies, or any other relevant constraints.

5) Solve the mathematical programming model:

a. Apply an appropriate optimization algorithm (e.g., linear programming, integer programming, or constraint programming) to solve the formulated model.

b. Obtain the optimal ranking factors that maximizes the objective function while satisfying the constraints.

c. Make any necessary adjustments or refinements to the model or solution based on the evaluation.

This pseudo code provides a general outline of how Factor Analysis Job Evaluation can be combined with Mathematical Programming to ranking the factors with fuzzy cognitive map.

4. Fuzzy Cognitive Map (FCM)

FCMs provide a graphical representation of a system, where nodes represent variables or concepts, and directed edges represent the causal relationships between them. It is a computational modelling technique that represents the causal relationships and interdependencies between variables in a system. In an FCM, each node has a fuzzy set associated with it, which represents the degree of membership or influence of that variable. The edges between nodes are labelled with fuzzy weights, which indicate the strength and direction of the causal relationships. The fuzzy weights capture the degree of influence that one variable has on another, taking into account the uncertainty and imprecision inherent in human thinking and decision-making. This seminal paper by Bart Kosko introduces FCMs and explains their application in modelling complex systems using fuzzy logic [17].

The fuzzy logic framework allows for gradual and imprecise reasoning, enabling FCMs to handle complex systems with uncertain or ambiguous information. FCMs can be constructed based on expert knowledge or derived from data through learning algorithms. They are particularly useful in domains where there is a high degree of complexity, nonlinearity, and uncertainty. FCMs have been widely applied in various fields, including decision support systems, risk analysis, strategic planning, and organizational management. One important aspect of FCM development is the participatory method used to configure the system. In this method, the insights and knowledge of key stakeholders are leveraged to determine the concepts and their relationships in the FCM. These stakeholders, who possess expertise and experience in the domain, contribute their understanding of the system's functioning, interdependencies, and cause-and-effect relationships. Özesmi and Özesmi (2004) introduced FCMs as a qualitative modelling tool to represent complex systems and their dynamic behaviour [18]. FCMs utilize directed graphs, concepts, and the edges represent the causal relationships or influences between them. The strength and direction of these influences are typically represented using fuzzy logic or linguistic terms, allowing for a more flexible and subjective representation of the system dynamics. The values for the normalized adjacency matrix ($M = (m_{i,j})$) represent the strength of the connections between the variables in the FCM. Each element $m_{i,j}$ in the matrix represents the weight or strength of the connection from variable i to variable j, after normalization.

The network metrics provide quantitative measures of the FCM structure and characteristics. The analysis of these network indexes was performed using FCM Expert software, chosen for its comprehensive analysis options.

Here is a brief explanation of each metric:

$$T = \sum_j^N V_i V_j \tag{1}$$

It refers to the total number of connections or ties in the FCM, indicating the overall complexity of the network (eq.1).

$$D = \frac{T-(N-1)}{T_{max}-(N-1)} \tag{2}$$

Density measures the possible ties in the FCM. It reflects the interconnectedness or compactness of the network (eq.2).

$$Ad = \frac{\sum_j^N Ad_{in} + \sum_j^N Ad_{out}}{N} \tag{3}$$

Average Degree: It represents the average number of connections per variable in the FCM. It provides an indication of the average complexity or influence of each variable within the network (eq.3).

$$C_j = \frac{2e_j}{k_j(k_j-1)} \tag{4}$$

Clustering Coefficient: It measures the extent to which the variables in the FCM tend to cluster together, forming subgroups or modules. It quantifies the presence of local interconnectedness within the network (eq.4).

$$L = \frac{1}{N(N-1)} \sum_{i \neq j} P_{ij} \tag{5}$$

Average Shortest Path Length: It calculates the average number of steps or connections required to reach one variable from another in the FCM. It provides insights into the overall efficiency or distance between variables (eq.5).

$$F = \sum \frac{(C^* - C_i)}{max \sum (C^* - C_i)} \tag{6}$$

Network Centralization: It assesses the concentration of influence or centrality within the FCM network. It indicates the degree to which some variables are more central or influential compared to others (eq.6).

$$C_B(n_i) = \sum_{j<k} g_{jk} \frac{(n_i)}{g_{jk}} \tag{7}$$

Betweenest Centrality: It measures the importance or influence of a variable in connecting other variables within the network. It quantifies the extent to which a variable acts as a bridge or intermediary in the FCM (eq.7).

$$v_{i,t} = \int \left(v_{i,t} + \sum_{j=1}^{n-1} v_{i,t-1} m_{ij}\right) \tag{8}$$

Eq. 8 used for evaluate the relationship between variables. To conduct the analysis with FCM Expert (version 1-www.fcmexpert.net).

5. Case Study

In the study, the analysis focused on the static level of the system, exploring the configuration and relationships between variables. It involved system variables (V_1, V_2, ..., V_n), connections between variables (V_1, V_2, etc.), a state vector $S = (s_1, s_2, ..., s_n)$ representing the values of the variables (typically between 0 and 1), and a normalized adjacency matrix ($M = (m_{i,j})$) that specified the weights of directed links between variables Vi and Vj in the interval [0,1].

The fuzzy inference process consisted of two phases: initialization and iteration. In the initialization phase, the first simulation set the initial state of V_i with a weight of 1. The process was then iterated until the system reached a stable configuration, also known as a steady state [19]. This approach allowed for the examination of the system's behaviour and the assessment of its responses under different conditions, providing insights into how the variables interact and influence each other within the system

5.1. Identification of system variables

The variables in the table in Eraslan's study were used and various expert opinions were included in the evaluation of the effects of the variables on each other (in Figure 1) [20].

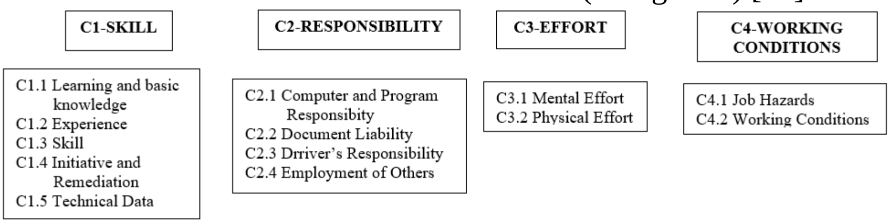

Figure 1: Criteria affecting the execution of processes in manufacturing

According to this table, criteria affecting workforce performance in production were determined as “Skill”, “Responsibility”, “Effort” and “Working Conditions”.

5.2. Identification of causal relations

The criteria determined and their relations with each other were evaluated by taking the opinions of field experts, and the averages of the impact degrees are shown in Table 1 below. The causal relation diagram is shown in Figure 2 below, taking into account the criteria determined in the previous step and expert opinions and the degree of influence. Considering the relationship status, the fuzzy cognitive map in Figure 2 was created together with the evaluations in Table 1. The following iteration results and final evaluation were obtained in the reference model run with the generated diagram.

Table 1: Averages of degrees of impact evaluated by experts

	C1.1	C1.2	C1.3	C1.4	C1.5	C2.1	C2.2	C2.3	C2.4	C3.1	C3.2	C4.1	C4.2
C1.1	1	0,8	0,6	0	0,7	0,3	0	0	0	0,6	0	0	0
C1.2	0	1	0	0	0	0,3	0,1	0	0	0,8	0,6	0	0,4
C1.3	0	0	1	0	0,8	0,6	0,6	0,4	0,3	0,2	0,1	0,1	0,1
C1.4	0	0	0	1	0	0	0	0,3	0,6	0	0,6	0	0,8
C1.5	0	0,8	0,6	0	1	0,6	0	0	0	0,4	0	0	0,3
C2.1	0,6	0,6	0	0	0,4	1	0,3	0	0	0,1	0	0	0
C2.2	0	0,8	0,6	0	0,3	0	1	0	0	0	0	0	0,1
C2.3	0	0,8	0,7	0	0,6	0	0	1	0,6	0,3	0,4	0,2	0,2
C2.4	0	0,5	0,5	0,6	0	0	0	0	1	0,7	0,7	0,8	0,3
C3.1	0,8	0	0	0	0,7	0,6	0,5	0	0,4	1	0	0	0,3
C3.2	0	0,6	0,6	0,5	0	0	0	0	0,3	0	1	0,5	0,8
C4.1	0	0,6	0,5	0	0	0	0	0	0,4	0	0	1	0
C4.2	0	0,7	0,6	0	0,5	0	0	0	0,4	0	0,3	0	1

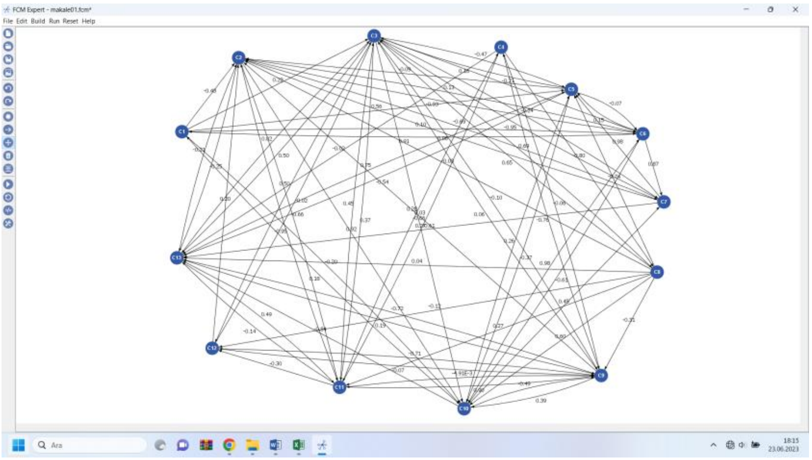

Figure 2: FCM network analysis

5.3. System analysis and simulation

The use of dynamic analysis in studying the evolution of possible scenarios is a valuable approach for understanding the impact of various factors, such as policy interventions, on a system. By manipulating the weights or values of specific variables during the simulation, it becomes possible to observe how these changes influence the system's behaviour over time. For example, by setting the weight of certain variables to their maximum level throughout the simulation, researchers can estimate the potential impact of policy interventions on the system. The changes observed in the system's behaviour, particularly in relation to variables that reach steady states, can then be interpreted as the outcomes of policy reinforcement.

This approach allows researchers to assess the effectiveness of different policies and understand how they contribute to the overall system dynamics. By analysing the evolution of scenarios under various conditions, policymakers can make informed decisions and adjust interventions based on their observed impacts. Overall, dynamic analysis provides a powerful tool for studying complex systems and evaluating the consequences of policy interventions in a simulated environment.

As a result of the final evaluation, the factor ranking result is given in Table 2 and the C5 factor with the highest value is 0,8454, while the C10 factor with the lowest value is 0,3937.

Table 2: FCM iteration results

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13
Step	C1.1	C1.2	C1.3	C1.4	C1.5	C2.1	C2.2	C2.3	C2.4	C3.1	C3.2	C4.1	C4.2
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
2	0.7397	0.3383	0.7406	0.5921	0.776	0.7246	0.5679	0.6099	0.3343	0.6308	0.7071	0.561	0.5263
3	0.8194	0.2041	0.8184	0.6613	0.8336	0.778	0.6439	0.6569	0.2605	0.5187	0.7541	0.5593	0.4984
4	0.8349	0.165	0.8296	0.695	0.8422	0.7628	0.6626	0.6671	0.2559	0.43	0.764	0.555	0.5253
5	0.833	0.1586	0.8307	0.7049	0.8446	0.7426	0.6568	0.6651	0.2589	0.3997	0.7695	0.5529	0.5538
6	0.8294	0.1587	0.8317	0.7073	0.8455	0.7328	0.6505	0.663	0.2587	0.3938	0.7731	0.552	0.5667
7	0.8275	0.1593	0.8326	0.7082	0.8455	0.7295	0.6476	0.6623	0.2576	0.3934	0.7745	0.5515	0.5706
8	0.8268	0.1596	0.833	0.7086	0.8454	0.7288	0.6467	0.6622	0.257	0.3937	0.7747	0.5514	0.5713

As can be seen from the figure 3, it is observed that the factor behaviours change in the dynamic environment after the 0.5 significance level assigned to all factors. Considering these ranking criteria, we can say that technical data, skill and tuition and basic, bodily effort are the most important criteria affecting the performance of the processes performed during production. At the same time, it is seen that the criteria of experience, occupational safety and responsibility of others and mental effort are insignificant criteria that do not affect (in Table 3).

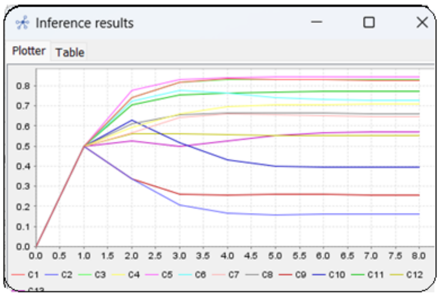

Figure 3: Iteration behavior diagram

Considering these ranking criteria, we can say that technical data, skill and tuition and basic, bodily effort are the most important criteria affecting the performance of the processes performed during production. At the same time, it is seen that the criteria of experience, occupational safety and responsibility of others and mental effort are insignificant criteria that do not affect (in Table 3).

Table 3: Ranking criteria value

Criteria No	Code	Criteria Definition	Ranking Value
C5	(C1.5)	Technical Data	0,8485
C3	(C1.3)	Skill	0,833
C1	(C1.1)	Learning and Basic Knowledgee	0,8268
C11	(C3.2)	Physical effort	0,7747
C6	(C2.1)	Computer and Program Responsibility	0,7288
C4	(C1.4)	Initiative and Remediation	0,7086
C8	(C2.3)	Driver's Responsibility	0,6622
C7	(C2.2)	Document Liability	0,6467
C13	(C4.2)	Working Conditions	0,5713
C12	(C4.1)	The Job Hazards	0,5514
C10	(C3.1)	Mental Effort	0,3937
C9	(C2.4)	Employment of Others	0,257
C2	(C1.2)	Experience	0,1596

6. Conclusion

Suggested systematic approach provides to measure and compare the value of jobs based on various factors such as skills, responsibilities, and working conditions. The study examined the job evaluation practices in the manufacturing industry, specifically focusing on production roles. It analysed different job evaluation methods used by organizations and their effectiveness in accurately assessing the value of production jobs.

Furthermore, FCMs provide decision support by evaluating alternative strategies, analysing the consequences of decisions, and identifying optimal courses of action to enhance job evaluation efficiency and resilience.

The findings revealed that a combination of quantitative and qualitative job evaluation with FCM methods yielded the most accurate and reliable results for production roles. This approach took into account both measurable factors such as productivity and output, as well as qualitative aspects like problem-solving abilities and teamwork.

Overall, the case study demonstrates that the application of FCMs in job evaluation offers a holistic and dynamic approach to understanding and improving job analysis management. The evolution of FCMs has enhanced their capabilities, allowing for a more comprehensive representation of supply chain complexities and supporting decision-making processes in an uncertain and dynamic environment. Finally, the study acknowledged that job evaluation is just one component of a comprehensive talent management strategy. It should be integrated with other HR practices, such as performance management, training and development, and succession planning, to create a holistic approach to managing and optimizing talent in the manufacturing industry.

References

[1] Suwarsono, L. W., Aisha, A. N., Nugraha, F. N. (2019), Comparison of Job Evaluation Methods: Implications for the Salaries Design in Publishing Company, Advances in Intelligent Systems Research, volume 173, 1st International Conference on Engineering and Management in Industrial System (ICOEMIS 2019), pages={305-312}, doi= {10. 2991/icoemis-19. 2019. 42}, publisher={Atlantis Press)

[2] Kahya, Emin. (2018). A wage model consisted of job evaluation, employee characteristics and job performance. Pamukkale University Journal of Engineering Sciences. 24. 720-729. 10. 5505/pajes. 2017. 92609.

[3] Morgeson, Frederick & Campion, Michael & Maertz, Carl. (2001). Understanding Pay Satisfaction: The Limits of a Compensation System Implementation. Journal of Business and Psychology. 16. 10. 1023/A:1007848007459.

[4] Chen Y, Zhang Z, Zhou J, Liu C, Zhang X, Yu T. (2023). A cognitive evaluation and equity-based perspective of pay for performance on job performance: A meta-analysis and path model. Front Psychol., Jan 20;13:1039375. doi: 10. 3389/fpsyg. 2022. 1039375. PMID: 36743591; PMCID: PMC9897207.

[5] Aliku, H. H., Morka, T. O., Igemohia, F. (2020) Compensation Management and Employee Performance: Manufacturing Industry in Focus-- Palarch's Journal of Archaeology of Egypt/Egyptology 17(7), 8792-8810. ISSN 1567-214x.

[6] Kozlowski, S. W. J., & Ilgen, D. R. (2006). Enhancing the Effectiveness of Work Groups and Teams. Psychological Science in the Public Interest, 7(3), 77–124. https://doi. org/10. 1111/j. 1529-1006. 2006. 00030. x

[7] Zhenjing G, Chupradit S, Ku KY, Nassani AA, Haffar M. (2022). Impact of Employees' Workplace Environment on Employees' Performance: A Multi-Mediation Model. Front Public Health. May 13;10:890400. doi: 10. 3389/ fpubh. 2022. 890400. PMID: 35646787; PMCID: PMC9136218.

[8] Ergu, D., Kou, G., Shi, Y., & Shi, Y. (2014). Analytic network process in fuzzy cognitive maps to model causality in decision-making. European Journal of Operational Research, 232(3), 658-668.

[9] Piera Miquel, M., Nebot, À., & Aler, R. (2019). Fuzzy cognitive maps as a decision support tool for environmental management: A systematic literature review. Science of the Total Environment, 650, 2405-2419.

[10] Karyotis, C., Pappis, C., & Stylios, C. D. (2021). Fuzzy cognitive maps in forecasting and decision-making: A systematic literature review. Information Sciences, 541, 165-195.

[11] Díaz-Madroñero, M., & Sánchez-Medina, J. J. (2017). Application of fuzzy cognitive maps for decision-making in the energy sector: A systematic review. Energies, 10(2), 166.

[12] Wu, J., & Lin, C. (2016). A literature review on the applications of fuzzy cognitive maps for representing complex systems. Expert Systems with Applications, 55, 228-241.

[13] Liu, Y., Chen, G., Li, S., & Wang, Q. (2020). Fuzzy cognitive map-based decision support systems: A review. Information Sciences, 510, 297-314.

[14] Erkan, E. F., Uygun, O. (2020), Scenario based examination of institutional leaning using fuzzy cognitive maps, Computers & Industrial Engineering, Volume 147, 106642, https://doi. org/10. 1016/j. cie. 2020. 106642.

[15] Gkitzia, V., Apostolou, D., & Mentzas, G. (2018). Fuzzy cognitive map-based expert systems: A review. Expert Systems with Applications, 107, 111-129

[16] Delen, D., & Walker, G. (2019). Fuzzy cognitive maps in healthcare: A systematic literature review and bibliometric analysis. Artificial Intelligence in Medicine, 95, 23-38

[17] Kosko, B. (1986), Fuzzy cognitive maps, International Journal of Man-Machine Studies, Volume 24, Issue 1, pp. 65-75, https://doi. org/10. 1016/S0020-7373(86)80040-2.

[18] Özesmi, U., Özesmi, S. L. (2004). Ecological models based on people's knowledge: a multi-step fuzzy cognitive mapping approach, Ecological Modelling, Vol. 176, Is. 1–2, pp. 43-64

[19] Falcone, P. M., et al. (2018). Dynamics of an olive oil bio-refinery in Andalusia: A multi-objective multi-agent approach. Sustainability, 10(3), 612.

[20] Eraslan, E., Arıkan, A (2004). Point method in remuneration, seniority and success evaluation: Application in the internal production department of a manufacturing company. Journal of Gazi University Faculty of Engineering and Architecture, 19(2), 139 - 150. (ın Turkish)