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Fuzzy Logic-based Recruitment System: An Innovative Solution for HR Departments

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Abstract— **Recruiting the best candidates has become a significant challenge for Human Resources (HR) departments due to the competitive job market and the stringent guidelines and standards they adhere to. In the Information Technology (IT) industry, where technical skills are crucial, this challenge becomes even more daunting. In this article, we propose a fuzzy logic-based recruitment system to support HR departments in making more nuanced and informed decisions. Our proposed system considers several factors, including education, experience, technical abilities, and interpersonal skills, to identify the most suitable candidate for an IT role. We present a systematic approach for incorporating the fuzzy logic controller into the recruitment process, which will offer HR managers clear recommendations based on precise calculations. By leveraging this framework, HR departments can achieve better decision-making outcomes, ultimately resulting in successful recruitment processes.**

Keywords— Fuzzy Logic; Fuzzy interference System (FIS); IT Recruitment; Decision Making.

I. INTRODUCTION

Recruiting the ideal candidate for an open position is a crucial task for any organization, especially in the Information Technology (IT) industry, where technical expertise is highly valued. The hiring process for IT positions is challenging due to the diverse skillsets that candidates bring across various platforms and languages. A prolonged hiring cycle can result in high-quality candidates being snatched up by other companies. To address this issue, firms have begun to consider reducing the hiring cycle from weeks to days as an essential step toward successful recruitment [1]. In this context, implementing a fuzzy logic decision-making system can prove highly beneficial. Such a system can help HR departments streamline the hiring process and identify the most suitable candidate efficiently. This article proposes the use of a fuzzy logic decision-making system that will consider several factors, including education, experience, technical abilities, and interpersonal skills, to identify the most suitable candidate for an IT role. By leveraging this system, HR departments can achieve faster and more efficient recruitment processes, ultimately leading to successful hiring outcomes.

Fuzzy logic is a mathematical system that enables the representation and manipulation of imprecise or uncertain concepts, making it an excellent fit for decision-making in situations where data is incomplete or uncertain [2]. The use of fuzzy logic can aid in the evaluation of IT candidates and assist in making informed hiring decisions. This report aims to provide an overview of fuzzy logic and its application in the hiring process, as well as the advantages and challenges associated with this approach. Lotfi Zadeh, a mathematician from the University of California, first introduced fuzzy logic in 1965 [3]. The fundamental idea behind fuzzy logic is to replace traditional binary logic (true or false) with degrees of truth between 0 and 1. This system can handle ambiguous or uncertain data by assigning membership grades or degrees of membership to the elements of a set. The power of fuzzy logic lies in its ability to deal with imprecision and uncertainty, which are inherent in many real-world problems [4]. Fuzzy logic has been widely applied in various fields, including control systems, decision-making, and pattern recognition [5]. One of the most significant advantages of fuzzy logic is its ability to capture and represent human reasoning and decision-making processes, which are often imprecise and uncertain. This characteristic makes fuzzy logic particularly useful in situations where conventional mathematical models fail to provide adequate solutions [6]. In the context of IT candidate evaluation, fuzzy logic can be employed to assign a definitive score to represent the candidate's skills after initial screening and testing processes are completed. By leveraging this approach, HR departments can achieve more accurate and nuanced decision-making outcomes. The following sections will outline the advantages and challenges associated with using fuzzy logic in the hiring process and provide recommendations for successful implementation.

Fuzzy inference controllers (FICs) are a type of fuzzy logic system that enables decision-making or system control using linguistic variables and a set of rules. The FIC consists of three main components: fuzzification, inference, and defuzzification. Fuzzification transforms input data into linguistic variables, which are then used to generate a set of fuzzy rules in the inference process. Defuzzification aggregates the results of the fuzzy rules to generate a crisp output value. Fuzzy inference controllers have been widely applied in diverse fields, including robotics, process control, and image processing. For example, FICs have been used to control robot motion and regulate complex industrial processes, as well as improve image segmentation and classification [7]. In process control, fuzzy inference controllers have been used to regulate and optimize the control of complex industrial processes, such as chemical plants and power systems [8]. In image processing, fuzzy inference controllers have been applied to improve the segmentation and classification of images [9]. One notable application of fuzzy inference controllers is in the development of intelligent transportation systems (ITS). Fuzzy inference controllers have been used to control traffic signals and reduce congestion on roads [10]. For example, a fuzzy logic-based traffic signal controller was used in the city of Barcelona to optimize traffic flow and reduce travel time for commuters [11]. Fuzzy inference controllers have proven to be effective tools in decision-making and control across a variety of fields,

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such as robotics, process control, image processing, and intelligent transportation systems. Therefore, it is reasonable to consider utilizing these controllers in the recruitment process of IT candidates.

II. RELATED WORK

Numerous studies have been conducted around HR recruitment processes. Among these studies is one that suggests a novel approach to selecting competent job candidates by utilizing the Fuzzy Simple Additive Method (FSAW) to overcome challenges faced by decision makers during recruitment. The FSAW system assigns a fuzzy number to each selection process to enable the selection of qualified applicants whose natural tendencies align with the job requirements. The system also considers the applicant's temperament and skills to ensure the right candidate is selected, as hiring the wrong person can result in a waste of valuable resources [12]. Another research proposed a personnel selection system using the Fuzzy Simple Additive Weighted (FSAW) Method to address the subjectivity in the selection process and consider the applicant's temperament. The study developed a three-level model to handle the database, applicant conditions, and ranking of applicants according to suitability. The research emphasized the importance of considering a candidate's natural tendencies and abilities to ensure they perform the job effectively, resulting in high organizational performance when the best candidates are selected [13]. A different research project had the objective of creating a Fuzzy Logic Expert System that can manage personnel selection and recruitment at Kings University College, which is a private academic institution located in Ghana. The process involved the creation of a fuzzy logic algorithm and its corresponding flowchart, both of which were simulated using MATLAB 7.8.0 (R2009a). To test the effectiveness of the system in personnel selection, the Chief Security Portfolio was utilized, and it successfully and efficiently identified qualified personnel from a pool of 16 applicants who were randomly selected from the university [14]. As human resources have been recognized as a crucial source of competitive advantage for organizations, finding the right candidate has become a vital function in human resource management, therefor one research presented the use of mamdani and sugeno type fuzzy inference system modeling techniques in group decision making within a fuzzy environment. Two top managers in a prominent Turkish business organization evaluated candidates for the position of mechanical maintenance manager using linguistic variables, which were then transformed into triangular fuzzy numbers. Prediction models were created using the fuzzy logic and ANFIS toolboxes of MATLAB, and their performances were compared. This study concluded that various fuzzy logic models are significantly suitable for accurately and effectively selecting candidates in the human resource selection process through fuzzy multicriteria group decision making [15]. Fuzzy multicriteria decision-making (MCDM) is a methodology used to support decision-making processes that involve multiple criteria, which may be conflicting or uncertain. Based on MCDM methodology, a fuzzy MCDM was used in the context of selecting human resources for a Greek private bank to evaluate and compare the suitability of different candidates based on various criteria. The following steps had been taken to implement a fuzzy MCDM methodology for selecting human resources: The first step was identifying the criteria that are relevant to the selection process. These criteria may include education, experience, skills, personal qualities, and others. The next step was determining their relative importance. The weights can be determined by using a variety of methods, such as pairwise comparisons or the analytic hierarchy process (AHP). The next step was evaluating each candidate on each of the criteria. This can be done using a rating scale, such as a Likert scale, or by assigning numerical scores. Then fuzzy logic was used to account for the uncertainty and imprecision in the data. This involved defining fuzzy sets for each criterion and applying fuzzy operations to determine the fuzzy performance scores for each candidate. After that, the fuzzy performance scores for each candidate can be aggregated using a variety of fuzzy aggregation methods, such as the weighted average or the ordered weighted average (OWA). Finally, the candidates can be ranked based on their aggregated fuzzy performance scores. The candidate with the highest score is considered the best fit for the job. So, by using a fuzzy MCDM methodology, a Greek private bank can make more informed and objective decisions when selecting human resources. The methodology allowed for the consideration of multiple criteria and the incorporation of uncertainty and imprecision in the data, which can lead to better hiring decisions and improved overall performance [16]. The quality of staff directly affects the effectiveness of any organization, which has led to a growing interest in university academic staff selection, therefore the process of selecting suitable academic staff is complex and involves considering multiple criteria for optimal decision making. The Analytic Hierarchy Process (AHP) is a Multi-Criteria Decision Making (MCDM) model that helps deal with decision-making problems affected by several conflicting factors, and it is useful for selecting the best alternative based on specific criteria, but academic staff selection presents uncertainties, and AHP lacks the ability to deal with imprecise and subjective judgment in its pair-wise comparison process. To overcome this problem, the Fuzzy AHP model used triangular fuzzy numbers (TFNs) and linguistic variables to improve accuracy and consistency in decision-making. A system architecture was developed using this model to solve problems. One research suggested using Chang's synthetic extent analysis with TFNs to improve decision-making by incorporating a range of values that account for DMs' uncertainty instead of a single crisp value. A numerical example based on work experience, academic background, and individual skill presented three alternative candidates, and the results indicated that the candidate with the highest normalized weight was the most suitable for employment. This research has practical implications for universities and organizations looking to improve their recruitment process by making it fair and efficient [17]. In another paper, the authors examined the relationship between recruitment techniques and computer science. They proposed a novel approach called the Intelligent Recruitment System (IRS), which involved several components. The first component was a resume classification and ranking system that uses deep learning and natural language processing (NLP) techniques. The second component was an Automatic Question Generation (AQG) system that measures an applicant's technical proficiency using a merged ontology designed from web and local sources. The third component measured soft skills by asking questions about different skill sets and comparing the applicant's answers to predefined answers using both syntactical and semantic similarity measurements. The final output of the IRS was a combination of these input parameters. The authors proposed a fuzzy inference system

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(FIS) and Mamdani's method to make decisions based on the final total score of each parameter and maximum quota. If multiple candidates receive the same final total score, the authors suggested using the FIS approach to help decision makers choose the most qualified applicant and avoid potential issues [18].

III. PROBLEM STATEMENT

As the demand for IT professionals increases due to the rapid pace of technological advancements, hiring IT staff has become a challenging task for organizations. The limited availability of capable candidates with the requisite skills and experience has resulted in a highly competitive job market, making it difficult for organizations to find suitable candidates. Moreover, the recruitment process can be costly and time-consuming, especially when competing with other companies for top talent. Another challenge is ensuring that the IT staff hired possess the necessary soft skills, such as communication, teamwork, and problem-solving, in addition to technical expertise, to meet the organization's requirements. Retaining IT staff can also be challenging as they may receive attractive job offers from other companies or feel dissatisfied with the organization's work conditions or growth opportunities.

The main objective of this research is to develop a Fuzzy decision-making system that can be used by organizations to hire IT personnel after conducting an initial testing phase.

IV. METHODOLOGY AND SYSTEM DEVELOPMENT

The proposed methodology involves the utilization of a fuzzy inference system to aid the requirement team in reaching a final decision, following the completion of an initial testing phase. Specifically, this system will be used to evaluate potential candidates for an open position of an "Intermediate level Backend Python Developer" in an existing team. Each candidate will be initially evaluated based on attributes such as age, education, experience, coding skills, and teamwork.

A. Attributes

After considering the information, the final attributes for the system will be Experience, Education, Coding Skills, and Teamwork. Age and Experience serve a similar purpose, and hence Age will be removed from the attributes list. Experience will be represented by a scale of 0 to 15 years to indicate the years of exposure a person has in the working environment. Education will still be considered an attribute as it represents a person's level of understanding on different programming topics. However, it will not be given as much importance as the other attributes. A person with long experience would be more valuable to the team than a highly educated person with minimal experience. Education will be represented by a scale of 0 to 8, based on the 9 qualification levels recognized by the governments of England, Wales, and Northern Ireland. In addition to Experience and Education, the final attributes for the system will include Coding Skills and Teamwork. The values for these attributes will be determined based on the candidate's performance in their test prior to this stage and will be aggregated to a scale of 0 to 10. Now that we have narrowed down our attributes to four and defined each of their universes of discourse, we need to determine the best membership functions that suit each input. Coding Skills will be given a high weightage in the final decision-making process, while Education will be given a lower weightage.

B. Membership Functions

In fuzzy logic, a membership function is a mathematical function used to describe the degree to which an element belongs to a particular set. Its purpose is to map input values to membership values between 0 and 1, where 1 indicates full membership and 0 indicates no membership.

For this system, the triangular and trapezoidal membership functions will be considered. These functions are often preferred when the membership of an element in a set is known to be high in the center of the set and low at the edges, making them useful for modeling uncertainty and imprecision in input data in fuzzy logic systems. As the position considered is for an Intermediate level, the applications are mostly expected to fall around the center of the universe of discourse.

For the Experience attribute, initially, a three triangular membership function was proposed. However, this caused the final output to produce results that did not suit the Intermediate position. To overcome this, the first two membership functions depicting "Novice" and "Experienced" were changed to a trapezoidal function as shown in Fig.1. This change will produce results favoring people with experience required for the expected job requirements.

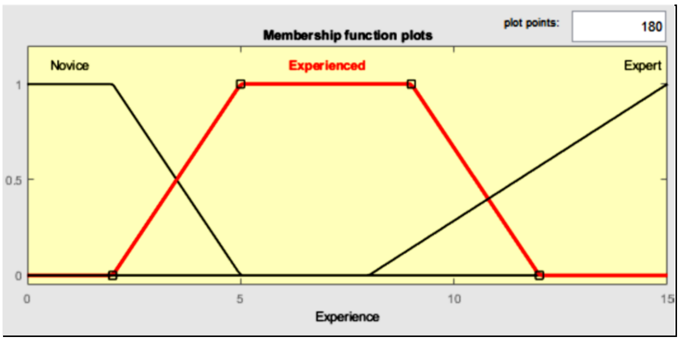

Fig. 1. Membership function graph for Experience input.

The education characteristic will feature three trapezoidal membership functions, namely "Moderate," "Good," and "Excellent" as shown in Fig.2. As we rely on the government-approved scale to determine each candidate's value, the scale becomes more stringent around the edges because the preferred education levels, such as Undergraduate and Master, are only a few points apart and appear as a clear set without decimal values.

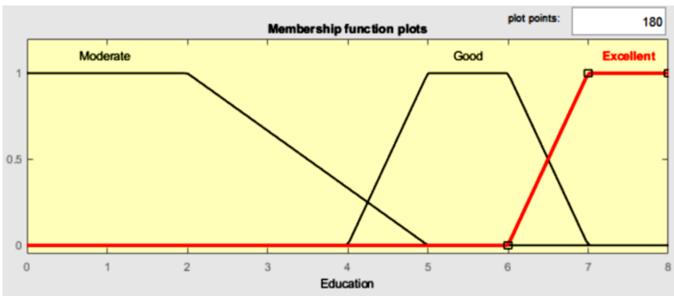

Fig. 2. Membership function graph for Education input.

The membership function labeled as "Moderate" encompasses candidates who have finished their GCSE or A-levels, or hold a Cert, albeit with a small degree of membership. Although this function may include more levels than necessary for some purposes, it is ideal for our goal, as it groups individuals who have completed a lower-level education into one category. The membership function denoted as "Good" includes candidates who have obtained certifications up to a master's degree, while the "Excellent" function encompasses those who have completed Honors or PHD degrees.

We have developed three membership functions, namely "Poor," "Moderate," and "Excellent," to assess the coding skills of an employee. Initially, we used trapezoidal membership functions, but the output did not meet our expectations for an intermediate position. Therefore, we changed them to triangular membership functions to introduce a sharp increase in the function. These membership functions describe the level of coding skills that are considered suitable for a specific IT position as shown in Fig.3. The "Poor" membership function indicates very limited coding skills, the "Moderate" membership function represents intermediate coding skills, and the "Excellent" membership function represents expert coding skills.

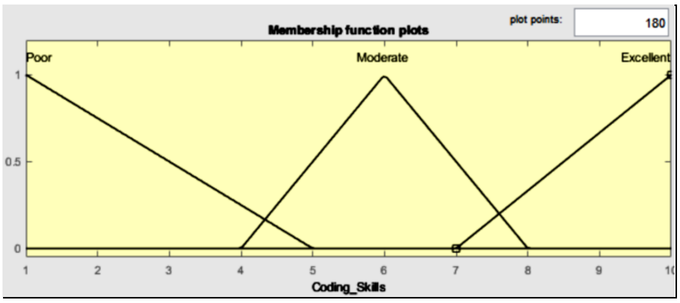

Fig. 3. Membership function graph for Coding Skills input.

The same approach can be applied to evaluate the team-work attribute as well. As mentioned earlier in the scenario, the organization is looking to hire an employee who can contribute to their existing team. Therefore, this attribute is equally important as coding skills in the recruitment process as shown in Fig.4.

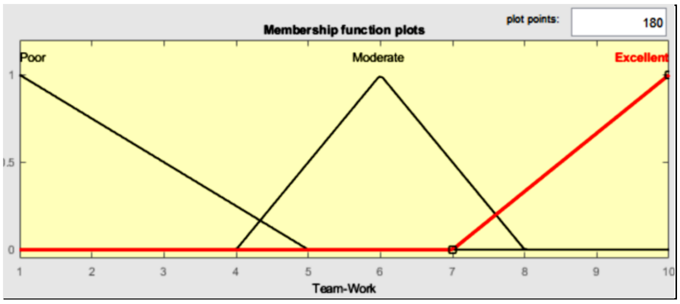

Fig. 4. Membership function graph for Team Work input.

The final output is referred to as "Decision," which initially comprised two membership functions, namely "Decline" and "Accept." Although this was suitable for the desired functionality, a third membership function called "Consider" was later added to identify candidates who could be considered for the next job opening as shown in Fig.5. The peak of this function is at 0.6, which categorizes candidates with a high score into this function, rather than considering them as an "average" pile. The output provides the organization with a linguistic variable as the final output. Additionally, it also provides a score ranging from 0 to 1, which can be used to make more precise decisions. The Gaussian membership function was used for this system as a clear, well-defined best case can be identified for each of the membership functions.

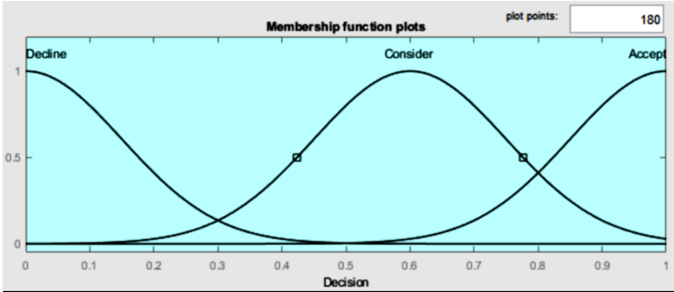

Fig. 5. Membership function graph for Decision output.

Table 1 clarifies the values of the three membership functions for all attributes, they were chosen after carefully going through job postings online and noting down the experience required for different work levels.

TABLE I. MEMBERSHIP FUNCTION VALUES FOR ALL ATTRIBUTES

Attribute Name	*MF Name*	*MF Type*	*MF Values*
Experience	Novice	Trapezoidal	[-5 0 2 5]
	Experienced	Trapezoidal	[2 5 9 12]
	Expert	Triangular	[8 15 20]
Education	Moderate	Trapezoidal	[-3 0 2 5]
	Good	Trapezoidal	[4 5 6 7]
	Excellent	Trapezoidal	[6 7 8 10]
Coding Skills	Poor	Triangular	[-5 1 5]
	Moderate	Triangular	[4 6 8]
	Excellent	Triangular	[7 10 12]
Team Work	Poor	Triangular	[-5 1 5]
	Moderate	Triangular	[4 6 8]
	Excellent	Triangular	[7 10 12]

Now that we have established a system for each attribute as inputs and the output, the next step is to establish rules for these inputs to generate the desired output.

C. Rules

As there are four different attributes with three membership functions each, generating a normal set of rules will result in 81 rules in total, which is not ideal. Moreover, we would have to adjust the rules to ensure that education does not impact the final decision as much as the other attributes. To simplify the rule set and ensure the best results for this scenario, we have reduced the number of rules to 49 by removing rules that produce similar outcomes and by prioritizing attributes that are more important than education.

The following set of rules has been designed to select the best candidate for an intermediate job opening to join a team, based on the four input variables: experience, education, coding skills, and teamwork. The membership functions for each of these inputs are:

- Experience: Novice, Experienced, Expert.
- Education: Moderate, Good, Excellent.

- Coding Skills: Poor, Moderate, Excellent.
- Teamwork: Poor, Moderate, Excellent.

The output of the system is a decision, which is represented by the following membership function:

- Decision: Decline, Consider, Accept.

The rules are arranged in a way that the most favorable combinations of input values result in the highest output values, which is "accept" in this case. The rules are designed in such a way that they prioritize the attributes that are more important for the job opening, and they provide a clear and concise decision based on the inputs. For instance, the first rule suggests that if a candidate possesses expert experience, excellent education, excellent coding skills, and excellent teamwork, then the decision is to "accept" as it represents an exceptional choice. Similarly, the second rule suggests that if a candidate has expert experience, excellent education, excellent coding skills, and moderate teamwork, then the decision is also "accept" as it is a strong choice. The rules are structured hierarchically, with the most desirable input value combinations being presented at the top. This guarantees that the system will prioritize the most desirable candidates before considering those who are less desirable. Education has a lower impact on the decision-making process compared to other input variables in the provided set of rules as it is listed later. Therefore, the system will evaluate the input values for experience, coding skills, and teamwork first before considering the education value. In the first rule, a candidate's education level is not a determining factor if they possess expert experience, excellent coding skills, and excellent teamwork. In this case, the candidate is considered an exceptional choice and is accepted. Similarly, in the second rule, a candidate's education level is also not considered if they possess expert experience, excellent coding skills, and moderate teamwork. The candidate is considered a strong choice and is accepted. This approach allows for consideration of candidates with less education if they excel in other areas, while candidates with higher education may not be accepted if they are lacking in other crucial areas. The set of rules provided aims to select the optimal candidate for an intermediate job opening by evaluating their experience, education, coding skills, and teamwork. However, the rules assign less importance to the education input compared to the other input variables, indicating that it has a lower influence on the decision. This suggests that other factors such as experience, coding skills, and teamwork may carry more weight in the selection process for an intermediate job opening than a candidate's level of education.

D. Entire set of rules

1. ***If experience is expert, education is excellent, coding skills are excellent, and teamwork is excellent, then the decision is accept (exceptional choice).***
2. ***If experience is expert, education is excellent, coding skills are excellent, and teamwork is moderate, then the decision is accept (strong choice).***
3. ***If experience is expert, education is good, coding skills are excellent, and teamwork is excellent, then the decision is accept (strong choice).***
4. ***If experience is expert, education is good, coding skills are excellent, and teamwork is moderate, then the decision is accept (strong choice).***
5. ***If experience is expert, education is moderate, coding skills are excellent, and teamwork is excellent, then the decision is accept (strong choice).***
6. ***If experience is expert, education is moderate, coding skills are excellent, and teamwork is moderate, then the decision is accept (strong choice).***
7. ***If experience is experienced, education is excellent, coding skills are excellent, and teamwork is excellent, then the decision is accept (strong choice).***
8. ***If experience is experienced, education is excellent, coding skills are excellent, and teamwork is moderate, then the decision is accept (strong choice).***
9. ***If experience is experienced, education is good, coding skills are excellent, and teamwork is excellent, then the decision is accept (strong choice).***
10. ***If experience is experienced, education is good, coding skills are excellent, and teamwork is moderate, then the decision is accept (strong choice).***
11. ***If experience is experienced, education is moderate, coding skills are excellent, and teamwork is excellent, then the decision is accept (strong choice).***
12. ***If experience is experienced, education is moderate, coding skills are excellent, and teamwork is moderate, then the decision is accept (strong choice).***
13. ***If experience is experienced, education is moderate, coding skills are moderate, and teamwork is excellent, then the decision is consider (strong choice).***
14. ***If experience is experienced, education is moderate, coding skills are moderate, and teamwork is moderate, then the decision is consider (strong choice).***
15. ***If experience is novice, education is excellent, coding skills are excellent, and teamwork is excellent, then the decision is consider (strong choice).***
16. ***If experience is novice, education is excellent, coding skills are excellent, and teamwork is moderate, then the decision is consider (strong choice).***
17. ***If experience is novice, education is good, coding skills are excellent, and teamwork is excellent, then the decision is consider (moderate choice).***
18. ***If experience is novice, education is good, coding skills are excellent, and teamwork is moderate, then the decision is consider (moderate choice).***
19. ***If experience is novice, education is moderate, coding skills are excellent, and teamwork is excellent, then the decision is consider (moderate choice).***
20. ***If experience is novice, education is moderate, coding skills are excellent, and teamwork is moderate, then the decision is consider (moderate choice).***
21. ***If experience is novice, education is moderate, coding skills are moderate, and teamwork is excellent, then the decision is consider (moderate choice).***
22. ***If experience is novice, education is moderate, coding skills are moderate, and teamwork is moderate, then the decision is consider (moderate choice).***
23. ***If experience is novice, education is excellent, coding skills are moderate, and teamwork is excellent, then the decision is decline (moderate choice).***
24. ***If experience is novice, education is excellent, coding skills are moderate, and teamwork is moderate, then the decision is decline (moderate choice).***
25. ***If experience is novice, education is good, coding skills are moderate, and teamwork is excellent, then the decision is decline (moderate choice).***
26. ***If experience is novice, education is good, coding skills are moderate, and teamwork is moderate, then the decision is decline (moderate choice).***
27. ***If experience is novice, education is moderate, coding skills are poor, and teamwork is excellent, then the decision is decline (moderate choice).***

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 04, April-2023

28. *If experience is novice, education is moderate, coding skills are poor, and teamwork is moderate, then the decision is decline (moderate choice).*
29. *If experience is novice, education is good, coding skills are poor, and teamwork is excellent, then the decision is decline (weak choice).*
30. *If experience is novice, education is good, coding skills are poor, and teamwork is moderate, then the decision is decline (weak choice).*
31. *If experience is novice, education is moderate, coding skills are poor, and teamwork is excellent, then the decision is decline (weak choice).*
32. *If experience is novice, education is moderate, coding skills are poor, and teamwork is moderate, then the decision is decline (weak choice).*
33. *If experience is novice, education is excellent, coding skills are poor, and teamwork is excellent, then the decision is decline (weak choice).*
34. *If experience is novice, education is excellent, coding skills are poor, and teamwork is moderate, then the decision is decline (weak choice).*
35. *If experience is experienced, education is excellent, coding skills are poor, and teamwork is excellent, then the decision is decline (weak choice).*
36. *If experience is experienced, education is excellent, coding skills are poor, and teamwork is moderate, then the decision is decline (weak choice).*
37. *If experience is experienced, education is good, coding skills are poor, and teamwork is excellent, then the decision is decline (weak choice).*
38. *If experience is experienced, education is good, coding skills are poor, and teamwork is moderate, then the decision is decline (weak choice).*
39. *If experience is experienced, education is moderate, coding skills are poor, and teamwork is excellent, then the decision is decline (weak choice).*
40. *If experience is experienced, education is moderate, coding skills are poor, and teamwork is moderate, then the decision is decline (weak choice).*
41. *If experience is expert, education is excellent, coding skills are poor, and teamwork is excellent, then the decision is decline (weak choice).*
42. *If experience is expert, education is excellent, coding skills are poor, and teamwork is moderate, then the decision is decline (weak choice).*
43. *If experience is expert, education is good, coding skills are poor, and teamwork is excellent, then the decision is decline (weak choice).*
44. *If experience is expert, education is good, coding skills are poor, and teamwork is moderate, then the decision is decline (weak choice).*
45. *If experience is expert, education is moderate, coding skills are poor, and teamwork is excellent, then the decision is decline (weak choice).*
46. *If experience is expert, education is moderate, coding skills are poor, and teamwork is moderate, then the decision is decline (weak choice).*
47. *If coding skills are poor or teamwork is poor, then the decision is decline (weak choice).*
48. *If coding skills are excellent or teamwork is excellent, then the decision is accept (strong choice).*
49. *If coding skills are moderate or teamwork is moderate, then the decision is consider (strong choice).*

The rules required for the fuzzy decision-making system, as depicted in Fig.6 and Fig.7, are provided in their entirety. It is important to note that OR operators were incorporated into the last three rules to address any potential edge cases.

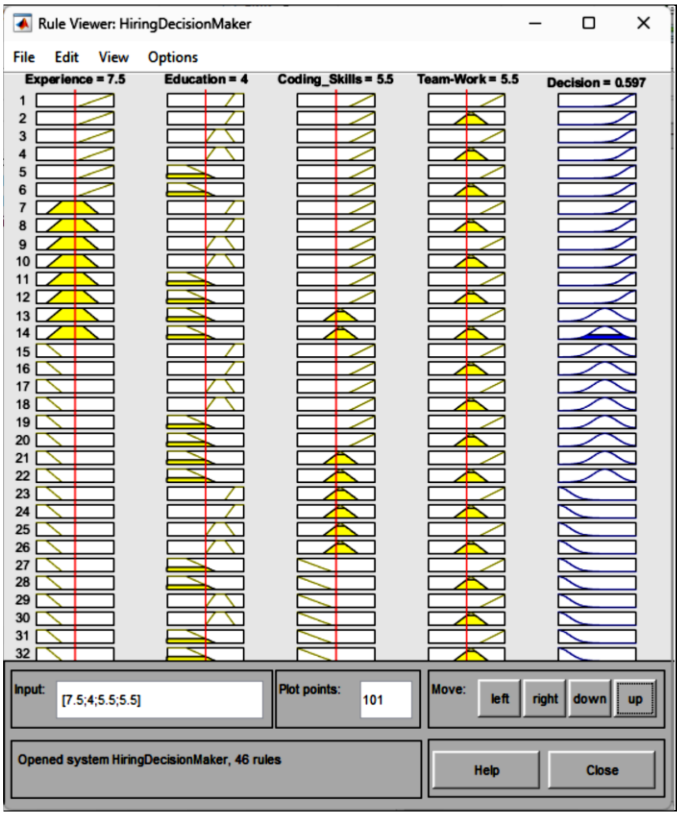

Fig. 6. Rule set list.

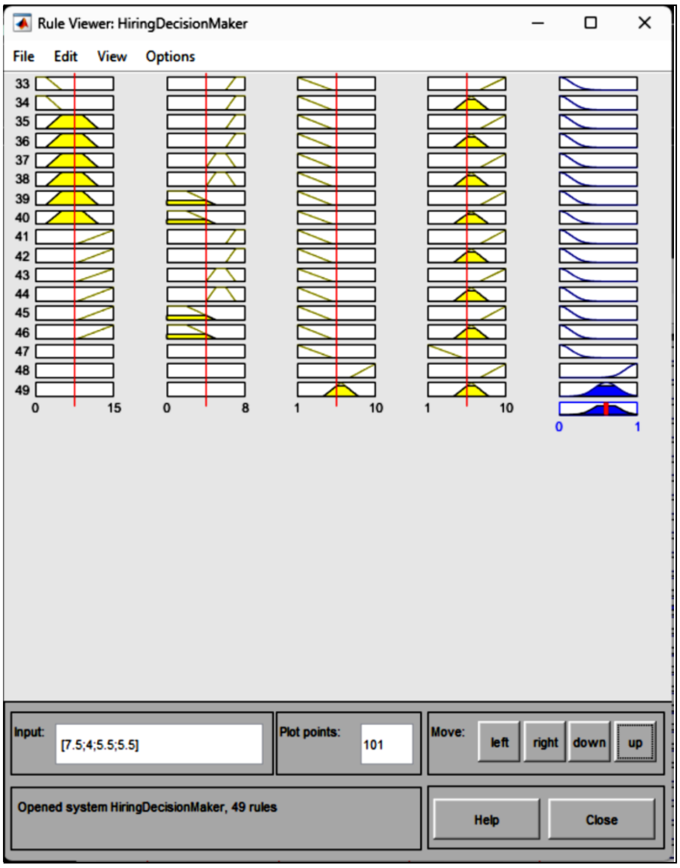

Fig. 7. Rule set list (continued).

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The hiring decision making system that use a fuzzy inference system (FIS) with Mamdani-based technique has been designed to assist HR in selecting the most suitable IT candidate for recruitment. This system incorporates four input variables: experience, coding skills, teamwork, and education. The output of the system is the overall suitability score of the candidate. The Mamdani-based technique is used to calculate the output based on the degree of membership of the inputs to the respective fuzzy sets. The system employs a set of rules organized in a hierarchical order, where the system prioritizes the most favorable input value combinations. Experience, coding skills, teamwork, and education are considered in the decision-making process, and the output is determined by the system's inference mechanism. The final output of the system provides a comprehensive evaluation of the candidate's suitability for the job. There are four input variables on the left side of the system, which each correspond to one of the criteria used to rank the applicant in a resulting HR selection score. Each of these input variables contains membership functions (as seen in Fig.1, Fig.2, Fig.3 and Fig.4), which are named after the applicant's key skills. The output variable is a synthesis of all the rules applied to the input variables, which ultimately produces the best rank level that satisfies all the fuzzy rules.

Fig.8 show the block diagram of the hiring decision making system based on the Mamdani method by using the MATLAB Version 7.7.0 and the results are discussed in the next section.

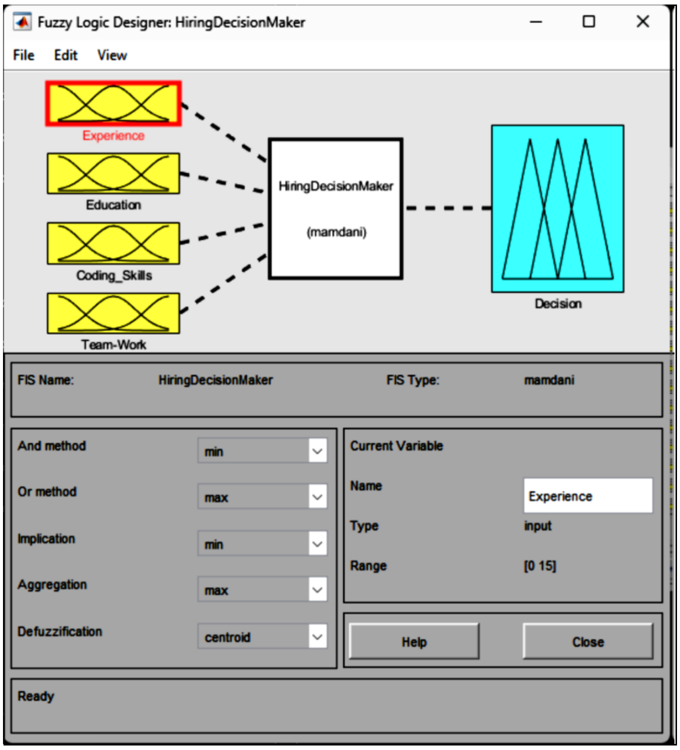

Fig. 8. Block diagram of the hiring decision making system by means of the Mamdani method, built in Matlab.

V. RESULTS AND DISCUSSIONS

Coding skills play an important part in the final decision of hiring a candidate for an intermediate job opening because they are directly related to the job responsibilities and requirements. Good coding skills ensure that the candidate will be able to perform the tasks and complete the projects efficiently and effectively. On the other hand, teamwork, education, and experience are also important factors to consider, but they may not be as directly related to the specific technical skills required for the job. For example, while teamwork is important for a candidate to be able to work well in a team environment, it may not be as crucial for their ability to complete the job tasks. Similarly, education and experience may provide a candidate with a foundation of knowledge and skills, but they may not necessarily translate to proficiency in the specific coding skills required for the job.

looking at the given graphs comparing coding skills to the other attributes as seen in Fig.9, Fig.10 and Fig.11, It is evident that individuals with significant experience or high levels of education are unlikely to be hired if they lack proficient coding skills. Furthermore, it is apparent that education does not have a significant impact on the final decision, aligning with our intended decision-making plan.

Now, let’s generate 25 random combinations of values for each attribute to simulate 25 candidates for that job. Each combination is generated randomly with no bias. The table contains 5 columns, first 4 denotes Experience, Education, Coding skills and Team work respectively. The 5th column denotes the decision value formulated by the final decision-making system as seen in Table II.

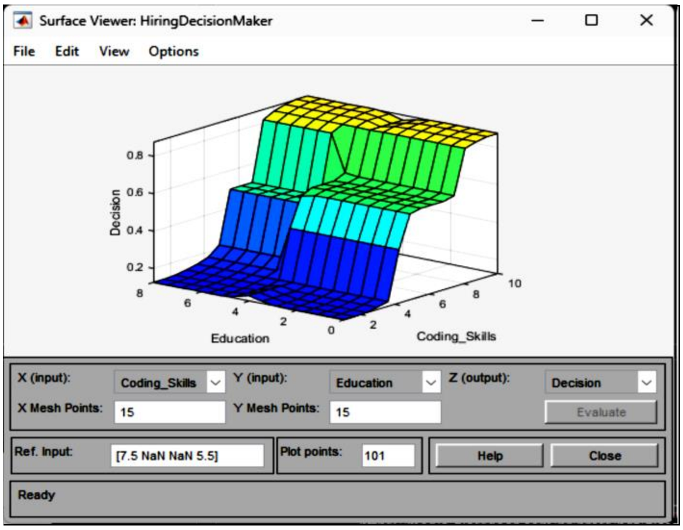

Fig. 9. Surface of Coding Skills against Education.

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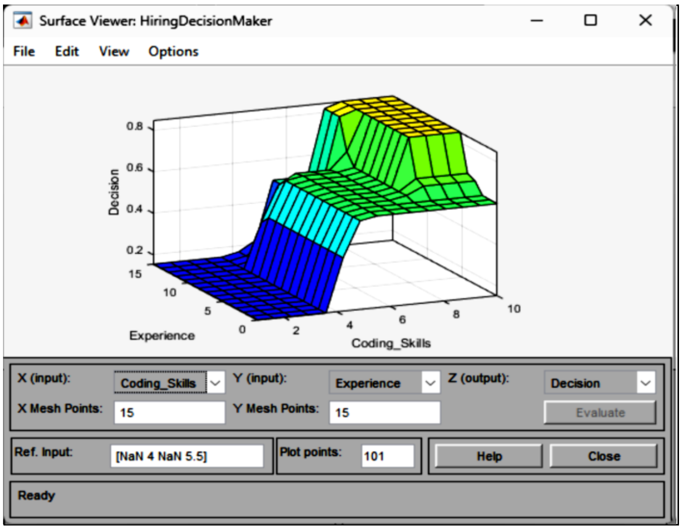

Fig. 10. Surface of Coding Skills against Experience.

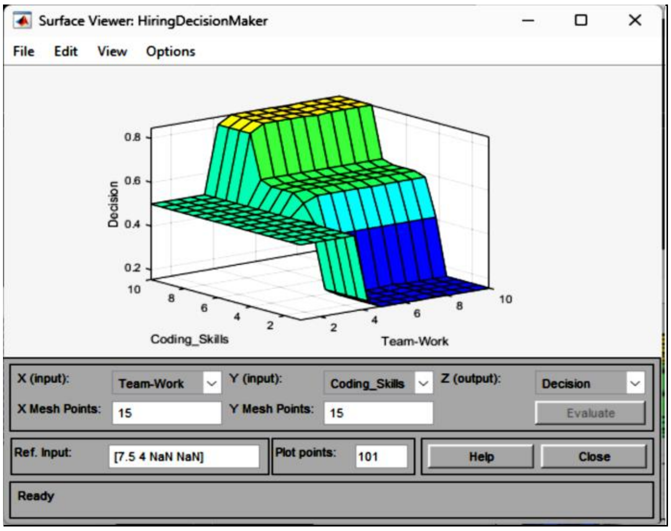

Fig. 11. Surface of Coding Skills against Experience.

The findings of our study reveal the efficacy of our system in selecting the most suitable candidate for the "Python Back-end Programmer" position. Upon analyzing the table, it is evident that the top-performing candidate out of the 25 randomly generated candidates has been accurately identified by our model, as highlighted in green. Despite possessing only a level 2 education, this candidate demonstrates exceptional coding skills, high teamwork scores, and extensive experience. Our analysis highlights the significance of coding skills in the selection process, while education level holds relatively less importance. These results suggest that our system has the potential to assist recruiters in identifying the most appropriate candidates for a given job position.

TABLE II. RANDOMLY GENERATED CANDIDATES

Experience	*Education*	*Coding Skills*	*Teamwork*	*Decision*
8	6	5	3	0.4493
7	**2**	**10**	**8**	**0.8835**
10	**8**	**7**	**10**	**0.7049**
3	5	1	2	0.1165
15	6	6	1	0.4388
9	7	4	5	0.5058
2	3	3	3	0.1403
14	5	4	6	0.5293
8	3	7	4	0.5058
4	7	6	5	0.5112
9	4	3	9	0.5381
8	6	2	8	0.3916
3	1	10	5	0.7049
6	8	4	2	0.1253
7	2	1	10	0.5000
1	5	8	2	0.3916
11	8	5	6	0.5985
12	7	3	8	0.4423
2	8	3	3	0.1403
8	1	4	3	0.1403
14	6	6	3	0.4827
9	3	5	1	0.3988
4	5	1	9	0.4611
5	**8**	**2**	**10**	**0.5248**
1	3	6	4	0.5293
15	7	3	5	0.4493

A comparison between the green and blue highlighted candidates indicates that our system prioritizes individuals with higher coding skills over other factors. On the other hand, a comparison between the same green candidate and the purple-highlighted candidate reveals that although the latter possesses the highest level of education attainable, they are given a lower score due to their poor coding skills.

VI. CONCLUSION

Utilizing fuzzy logic as a controller in the HR selection process for IT candidates presents a flexible and intricate approach to decision-making. Incorporating fuzzy logic enables HR to consider multiple factors, including technical expertise, communication proficiency, and personality traits, and assign appropriate weights to arrive at a more precise and comprehensive hiring decision. The suggested framework outlines a methodical process for integrating a fuzzy logic-based recruitment system.

REFERENCES

[1] Murray, J. P. (1999). Successfully hiring and retaining IT personnel. Information Systems Management, 16, 18-24.
[2] Zadeh, L. A. (1988). Fuzzy logic. Computer, 21(4), 83-93.
[3] Zadeh, L. A. (1965). Fuzzy Sets. Information and Control, 8(3), 338-353.
[4] Zadeh, L. A. (1973). Outline of a New Approach to the Analysis of Complex Systems and Decision Processes. IEEE Transactions on Systems, Man, and Cybernetics, 3(1), 28-44.
[5] Mendel, J. (1995). Fuzzy Logic Systems for Engineering: A Tutorial. Proceedings of the IEEE, 83(3), 345-377.
[6] Dubois, D., & Prade, H. (1980). Fuzzy Sets and Systems: Theory and Applications. New York: Academic Press.
[7] Mendel, J. M., & Liu, F. (1997). Applications of fuzzy control to robotics and process control: a survey. Fuzzy Sets and Systems, 90(2), 111-124.
[8] Cui, L., & Chung, F. L., (2000). Fuzzy modeling and control of complex industrial processes. IEEE Transactions on Fuzzy Systems, 8(2), 213-222.
[9] Zhang, L., & Liu, X. (2001). Fuzzy logic-based image segmentation. Journal of Electronic Imaging, 10(3), 791-798.
[10] Nunez, A., Saha, S., & Elizondo, D. (2014). Fuzzy inference system for traffic signal control in intelligent transportation systems. International Journal of Computer Science and Network Security, 14(2), 48-55.
[11] Oliveira, F., & Coelho, M. C. (2011). A fuzzy-logic-based traffic signal controller for urban networks. IEEE Transactions on Intelligent Transportation Systems, 12(2), 457-467.

[12] Zibs, D., & Kabari, L. (2020). Applicant Recruitment System Using Fuzzy Logic. International Journal of Computer Science and Mobile Computing, (9)8, 1-7.

[13] Samalia, V., Gumpy, J., & Manga, I. (2018). Application of fuzzy logic for personnel selection. International Journal of Computer Applications, 179(15), 21-5.

[14] Duodu, Q., & Hamidu, S. K. (2021). Fuzzy Expert System for Selecting and Recruiting Personnel. International Journal of Computer Applications, 183(28),1-5.

[15] Tinkir, M., Doganalp, B., & Doganalp, S. (2015). Human resource selection process by using various fuzzy logic techniques. In Proceedings of the Workshop on Foundations of Informatics (pp. 24-29).

[16] Polychroniou, P. V., & Giannikos, I. (2009). A fuzzy multicriteria decision-making methodology for selection of human resources in a Greek private bank. Career Development International, 14(4), 372-387.

[17] Asuquo, D. E., & Onuodu, F. E. (2016). A fuzzy AHP model for selection of university academic staff. International Journal of Computer Applications, 141(1), 19-26.

[18] Maddumage, C., Senevirathne, D., Gayashan, I., Shehan, T., & Sumathipala, S. (2019). Intelligent Recruitment System. In 2019 IEEE 5th International Conference for Convergence in Technology (I2CT) (pp. 1-6). IEEE.