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Employee Productivity Assessment Using Fuzzy Inference System

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Abstract: The success of an organization hinges upon the effective utilization of its human resources, which serves as a crucial developmental factor and competitive advantage, and sets the organization apart from others. Evaluating staff productivity involves considering various dimensions, notably structural, behavioral, and circumferential factors. These factors collectively form a three-pronged model that comprehensively encompasses the facets of an organization. However, assessing the productivity of employees poses challenges, due to the inherent complexity of the humanities domain. Fuzzy logic offers a sound approach to address this issue, employing its rationale and leveraging a fuzzy inference system (FIS) as a sophisticated toolbox for measuring productivity. Fuzzy inference systems enhance the flexibility, speed, and adaptability in soft computation. Likewise, their applications, integration, hybridization, and adaptation are also introduced. They also provide an alternative solution to deal with imprecise data. In this study, we endeavored to identify and measure the productivity of human resources within a case study, by developing an alternative framework known as an FIS. Our findings provided evidence to support the validity of the alternative approach. Thus, the utilized approach for assessing employee productivity may provide managers and businesses with a more realistic asset.

Keywords: productivity; human resources; fuzzy inference system (FIS); alternative approach

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1. Introduction

The productivity of employees holds significant importance within organizations, serving as a key performance indicator. Productivity, in general, refers to the ratio of output to inputs, including human resources (HR), financial and physical resources, strategic processes, and time. While technological and economic advancements are essential, they rely heavily on a skilled and capable workforce. However, managing employees is more challenging than financial or operational management, due to the intricate nature of human behavior [1]. Regrettably, in recent years, organizations have primarily focused on technological advancements to gain a competitive edge, often neglecting the proper attention required for their HR. Consequently, the appraisal of employees, the provision of constructive feedback, motivation, and continuous staff improvement, essential aspects for gaining a competitive advantage have been overlooked by many organizations [2]. Consequently, understanding employee attitudes within today's dynamic work environments presents a significant challenge for organizations [3]. Achieving high levels of work productivity at the individual level is crucial for organizations striving to enhance their overall performance and generate sustainable positive impacts [4]. Organizations seek effective strategies to improve employee productivity, which can be defined as the capacity of employees to achieve organizational goals by generating goods or services [5]. Trust within organizations also plays a significant role in employee productivity, as a lack of trust can adversely impact organizational performance [6]. Inspired by Maslow's hierarchy of needs, employees can thrive and achieve high efficiency in the workplace by fulfilling lower-level needs, such as spiritual needs, safety or security needs, job satisfaction, and self-esteem needs [7]. Consequently, organizations focus on performance management, and increasingly view performance appraisals as a valuable tool for effectively managing employee productivity [8]. However, the measurement and evaluation of employee productivity through performance appraisals often face challenges that obscure their impact on the organization's bottom line. These challenges include three types of errors: the first is the fact that 80–90% of the users achieve evaluations that are clearly above the average; in other words, this generosity error skews the results [9]. Secondly, evaluator teams may lack the necessary qualifications to accurately identify and assess specific factors related to employee productivity. Thirdly, the results can be biased or correlated due to political incentives present within organizations [10]. These errors and biases hinder the ability to derive meaningful insights from performance appraisal measurements. Fuzzy logic, recognized for its ability to handle ambiguity, is proving to be an effective technique for evaluating productivity aspects and aiding decision-making in the humanities. While crisp sets are commonly employed to represent ill-known values or situations precisely, similar to interval analysis or propositional logic, fuzzy sets provide a means to express uncertainty [11]. While crisp sets merely distinguish between conceivable and impossible values when representing uncertainty, fuzzy sets introduce gradations to soften the boundaries of the uncertainty sets. Consequently, fuzzy sets capture ambiguity, with rationales [12]. Fuzzy logic enables the utilization of natural language to convey human information effectively. For instance, the factor of "job satisfaction" within employee productivity can be expressed as a linguistic variable, where "high/low job satisfaction" represents different degrees. Fuzzy (If–Then) rules are commonly employed in fuzzy systems to describe linguistic variables in conditional statements, which consist of fuzzy logic. These rules are closely tied to the fuzzy inference system (FIS), which is formulated using fuzzy logic operators and fuzzy (If–Then) rules to determine the consistency of given rules, and enables decision makers to prioritize criteria effectively [13]. Building upon the aforementioned discussion, it becomes evident that employee development plays an integral strategic role in achieving economic growth. However, previous research in this domain has primarily relied on prioritizing productivity factors using researcher-made questionnaires or pairwise comparison methods. It is important to recognize that ambiguity often arises in critical strategic decisions, due to inherent limitations in evaluators' rationality and the available information about alternatives [14]. In light of this, the present study proposes using fuzzy logic to assess employee productivity. A fuzzy inference system offers an accurate projection of staff productivity. As managers responsible for strategic decision making may not possess technical expertise, this approach serves as an appropriate scheme to explain computation outcomes in an interpretable manner. Fuzzy systems have achieved notable success in various applications, effectively addressing a wide range of problems. This emerging trend in soft computing techniques enhances flexibility, speed, adaptability, integration, and hybridization. Moreover, it presents an alternative solution for handling imprecise data. The results obtained from the FIS model exhibit a robustness that is comparable to statistical methods, while promoting a more intuitive interpretation of employees' productivity. [15,16]. Thus, to present the feasibility of the suggested approach, this study identified the key productivity of employees within a case study of the Fars Regional Electric Company, and designed an FIS under skeptical conditions for evaluating these factors. This study is significant, because it proposes an alternative approach to assess productivity factors; it helps to improve decision making and organizational performance, while emphasizing the importance of employee productivity and addressing employee management challenges.

2. Literature Review

2.1. Productivity

Productivity refers to the accomplishment or effectiveness of a process or activity. In essence, it quantifies the number of products or services delivered by a company or organization. In macroeconomic terms, productivity plays a crucial role in driving structural progress, technological advancements, economic growth, and meeting the demands of globalization [17]. Organizational productivity is essential for maintaining competitiveness, as it enables companies to enhance their performance on both international and regional scales. Measuring and defining productivity can be a comprehensive task encompassing individual, organizational, and national levels. At the national level, productivity is often assessed using indicators such as labor, capital, raw materials, and gross domestic product (GDP). However, it is important to note that productivity should not be confused with performance or efficiency, even though these terms are sometimes used interchangeably. Performance refers to the accuracy of execution, while efficiency pertains to the execution of activities with accuracy. In other words, productivity can be viewed as the sum of the performance and efficiency components [18].

The productivity of human resources, however, is one of the most important concerns of any organization. When employees operate productively as members, their organization benefits overall. Human resource procedures have been found to affect attitudes and, in turn, the productivity of work environments [19]. The term "human resource management" encompasses the management of an organization's workforce, involving a range of procedures, systems, and policies that influence employees' attitudes, performance, and behavior. Human resource management involves various tasks, such as meeting human resource requirements, evaluating candidates, recruitment, training, providing rewards, and conducting employee assessments. Additionally, it entails managing workplace relationships, addressing health and safety issues, and addressing concerns related to fairness and justice [20]. Human resource management practitioners hold the responsibility of developing organizational human resources, and play key roles in building resources and capabilities. The productivity of human resources can be enhanced through various factors, including appropriate recruiting strategies, education, fostering beneficial relationships between personnel, designing effective reward structures, promoting job satisfaction, and providing different services for employees [21]. Simply increasing job positions does not guarantee improved productivity of human resources, but requires the presence of professional and experienced staff who possess the necessary capabilities to apply their knowledge in the workplace [22].

2.2. Fuzzy Inference System (FIS)

The probability measurement system, known as fuzzy logic, which is rooted in human thinking ability, is composed of a set of rules and an activation function. Fuzzy logic operates on a multi-valued framework, considering degrees of membership and degrees of truth, as opposed to the binary nature of two-valued Boolean logic. As highlighted by Zadeh, fuzzy logic operates on a continuum of logical values, ranging from 0 (completely false) to 1 (completely true). This advancement in the field of possibility theory, facilitated by fuzzy logic, enables the representation and manipulation of fuzzy concepts using natural language terms [23]. Fuzzy logic modeling is particularly useful in complex and highly ambiguous situations, providing a framework for modeling complex nonlinear relationships. It offers several advantages over traditional mathematical modeling, including a transparent reasoning mechanism, the incorporation of linguistic data from human experts, the integration of numerical and linguistic information, and the ability to evaluate complex nonlinear functions with simple models [24]. In designing fuzzy sets, there are various approaches to interpreting and analyzing subjective data, such as using fuzzy rating scale-based questionnaires. These questionnaires allow for the expression of human perceptions, using fuzzy rating scales known as linguistic variables [25]. An FIS is a powerful tool that transforms numerical variables into fuzzified ones. Fuzzification is the process of transforming crisp data into fuzzy sets or fuzzy values. The Takagi–Sugeno Fuzzy Model (Sugeno) and the Mamdani FIS are the two main types of FISs. The Sugeno model performs better than the Mamdani FIS in terms of computing efficiency, even though Mamdani collects human input more effectively [26]. Every FIS consists of four operational components:

- Fuzzification module: This module transforms crisp inputs into fuzzy sets using a fuzzification function.
- Knowledge base: The knowledge base stores IF–THEN rules provided by experts.
- Inference engine: The inference engine simulates the human reasoning process by making fuzzy inferences using the inputs and IF–THEN rules.
- Defuzzification module: The defuzzification module converts the fuzzy sets obtained from the inference engine into crisp values.

2.3. Research Background

Azizi et al., 2022, carried out research with the goal of identifying crucial elements and things that have an impact on the productivity of sustainable human resources in a railway operation company. The study's primary focus was on managers and staff members of the human resources division. As techniques for data analysis, the researchers used the correlation coefficient, multivariate regression, and component analysis. The results showed the primary elements and variables that the human resources department believed to be impacting worker productivity in the Urban and Suburban Railway Operation Company. These factors were primarily related to human resources management, motivation, and requirements for effective contribution to public welfare. Organizational attitude and culture, leadership style, bonuses, and ergonomics were identified as factors affecting productivity, or as independent variables [27]. In another study titled *Identifying and prioritizing the factors affecting human resource productivity in Chabahar Port*, Harati Mokhtari and Younespoor (2022) examined the most effective factors on human resource productivity, and prioritized them using the analytical hierarchy process method, which is a structured technique for organizing and analyzing complex decisions. Their research showed that the top five factors influencing manpower performance in Chabahar Port were management and leadership style, proportionality between personal interests and jobs, a staff promotion system based on competence, proportionality between individual skills and jobs, and work conscience. Additional factors that placed sixth to tenth in priority were the presence of acceptable wage systems, in-service training, pertinent education, optimal circumstances for professional advancement and promotion, and conformity to rules and regulations, respectively [28]. Oyefusi (2022) conducted a study titled *Team and Group Dynamics in Organizations: Effect on Productivity and Performance*. The study examined the impact of team and group dynamics on employee performance and productivity within a business setting. The objective of the study was to understand the variables influencing employee behavior, and their potential effects on output and performance. Additionally, the study identified that employee happiness could significantly influence performance and productivity, particularly in cases where the organization's principles are not effectively communicated, especially to new hires who may possess diverse temperaments, cultural backgrounds, socioeconomic circumstances, and religious beliefs. The study further revealed that leadership behavior and personality have the potential to shape organizational behavior, thereby impacting performance positively or negatively [29]. Delbari et al. (2020) identified the key factors affecting employee productivity and analyzed the situation among staff members at the Azad University of Qom and the University of Qom. The researchers collected data through semi-structured interviews and a researcher-made questionnaire from a sample of 331 individuals selected through stratified random sampling. The results showed that organizational and individual factors contributed to productivity, including goals, training, human relationships, organizational culture, job descriptions, appropriate relationships between jobs and their occupants, structure, and management. Additionally, social and economic environmental elements were noted. The results indicated that productivity factors had a mean score of 3.26, with individual factors scoring higher at 3.66, while organizational factors had the lowest mean score at 2.99 [30]. Diamantidis and Chatzoglou (2019) conducted a study entitled *Factors Affecting Employee Performance: An Empirical Approach*, employing a novel research technique that utilized structural equation modeling, and an investigation on the links between human resource parameters and employee performance. The findings revealed that job environment and management support had the most significant direct and indirect effects on job performance. Additionally, flexibility and intrinsic motivation were found to have a direct influence [31]. Guruprasad et al. (2016) conducted a study entitled *Fuzzy Logic as a Tool for Evaluation of performance appraisal of Faculty in higher education institutions*. He developed a fuzzy logic model in MATLAB using the MATLAB Fuzzy Logic Toolbox after creating an algorithm in Visual Basic (VB). The goal of the model was to forecast how significant each factor would be in gauging faculty performance. For similarity and comparison, the researchers generated fuzzy values and aggregated the weighted values of each category. This method offers interactive tools for accessing various functions through a graphic user interface, and provides 3-D visualization and fuzzy rule inference. The obtained results demonstrated that the utilization of an FIS as an intelligent engine can lead to human resource productivity improvements of more than 3000 percent in certain cases [32].

3. Methodology

The main goal of this study is to present an alternative approach aimed at assessing employee performance through the utilization of an FIS. Therefore, in order to assess the feasibility of the proposed approach, a case study was conducted. Six human resource experts of the Fars Regional Electric Company were extended an invitation to partake in this study. Table 1 classifies the employee factor based on three-pronged model.

Table 1. Productivity of employee factor based on three-pronged model.

Prong's Title		Factor	Definition
Structural Factors	Soft Factors	Management structure	The regulation and coordination of roles, authority, responsibilities, and information flow across different management levels
		Personality–job fit	A field of organizational psychology that argues that a person's personality qualities may provide insight into how adaptable they are to a certain environment
		In-service program	Professional development programs and knowledge-sharing platforms that facilitate training and idea exchange among professionals
	Hard Factors	Reward management	A strategic approach to incentivizing your workforce to improve performance, engagement, and morale
		Ergonomic design	Enhancing workplace design to accommodate employee needs and improve comfort
Behavioral Factors		Work motivation	The interplay of internal and external factors that shape and influence an individual's work-related behavior
		Job satisfaction	An indicator of how pleased employees are with their employment, including whether they enjoy all elements of their position or just some of them
		Personal skills	Assessing an individual's ability to interact effectively with others and their environment
Circumstantial Factors		Job security	Perceived assurance of maintaining one's current position in the foreseeable future or the sense of protection against
		Organizational culture	The collection of values, expectations, and practices that guide and inform the actions of all team members
		Economic stability	The absence of excessive fluctuations in the macroeconomics

The rest of this research was implemented in two steps. Firstly, the factors of the productivity of employees were extracted through academic information. Secondly, a questionnaire was prepared based on fuzzy rules. In this step, each question was categorized and classified to cover 126 fuzzy rules, including the number of inputs and the parameter membership of fuzzy blocks. We utilized Mamdani's compositional rule of inference model [33], which is one of the most commonly used fuzzy inference techniques. The center of area method (COA) was implemented for the defuzzification of the resulting fuzzy sets. The Mamdani fuzzy method takes crisp inputs and produces crisp outputs. Its performance relies on user-defined fuzzy variables and user-defined fuzzy rules. The underlying philosophy of this method is that humans can easily describe the rules for many systems in terms of fuzzy linguistic variables. Consequently, we can effectively model a complex nonlinear system by employing discernment rules with fuzzy variables. The Mamdani fuzzy inference system (FIS) is illustrated in Figure 1.

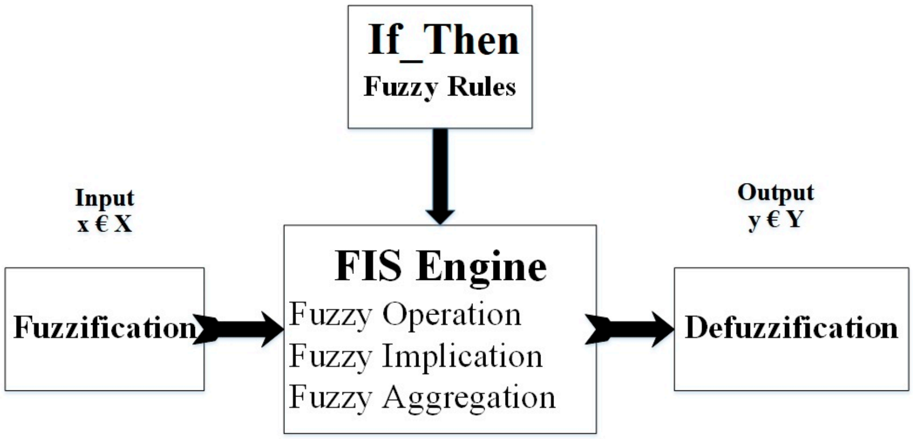

Figure 1. Mamdani FIS.

Each FIS engine/block in this method comprises the following operational steps: (1) membership function and operational operators, (2) fuzzy rules, and (3) defuzzification. In this research, we proposed a modified architecture for the FIS engines using the hierarchical FIS, which is described as follows:

- Membership function and operational operators:

Fuzzification serves as the initial step, in which the inputs are taken and their degree of belongingness to the appropriate fuzzy sets is determined through membership functions. A membership function is represented by a curve that maps each input point to a membership value ranging from 0 to 1. Various types of membership functions exist, such as triangular, trapezoidal, piecewise, Gaussian, bell-shaped, etc. For the proposed FIS, a triangular form is adopted for the membership function. This choice is made to facilitate the easier evaluation of the questions by the experts, as there is no provision for a triangular fuzzy number on an ordinal scale to accommodate the uncertainty of the interval boundaries [34]. The triangular fuzzy number is derived from a three-value judgment consisting of the minimum possible value 'a', the most probable value 'b', and the maximum possible value 'c' [35]. A triangular form of a fuzzy number can be denoted as $\widetilde{\mathrm{M}} = (a, b, c)$, as illustrated in Equation (1) and Figure 2.

$$\mu_M = \left\{ \begin{array}{cc} 0 & x \leq a \\ \frac{(x-a)}{(b-a)} & a \leq x \leq b \\ \frac{(c-x)}{(c-b)} & b \leq x \leq c \\ 0 & c \leq x \end{array} \right\} \quad (1)$$

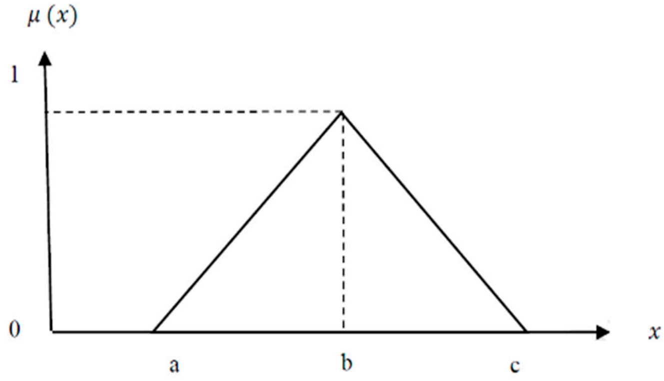

Figure 2. The triangular fuzzy membership function.

The linguistic terms assigned to each fuzzy set for inputs by the expert's evaluation are "poor", "average", and "good". Similarly, for the outputs, the linguistic terms are "very low", "low", "medium", "high", and "very high", as presented in Tables 2 and 3, and also illustrated in Figures 3 and 4, respectively [36].

Table 2. Parameters of input membership function.

Linguistic Variables	Fuzzy Number
Poor	(0, 0, 0.5)
Average	(0, 0.5, 1)
Good	(0.5, 1, 1)

Table 3. Parameters of output membership function.

Linguistic Variables	Fuzzy Number
Very Low	(0, 0, 0.25)
Low	(0, 0.25, 0.5)
Medium	(0.25, 0.5, 0.75)
High	(0.5, 0.75, 1)
Very High	(0.75, 1, 1)

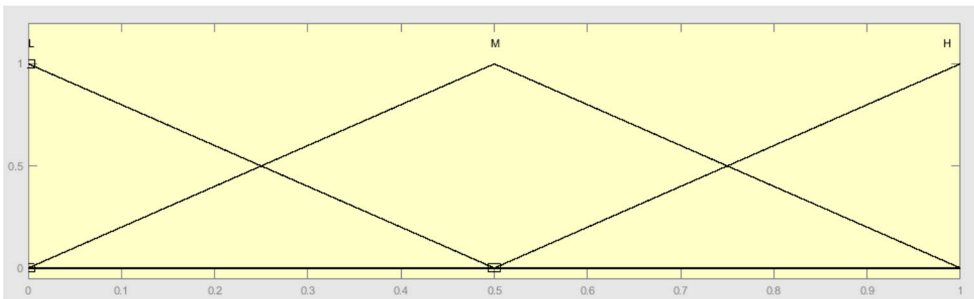

Figure 3. Input membership function.

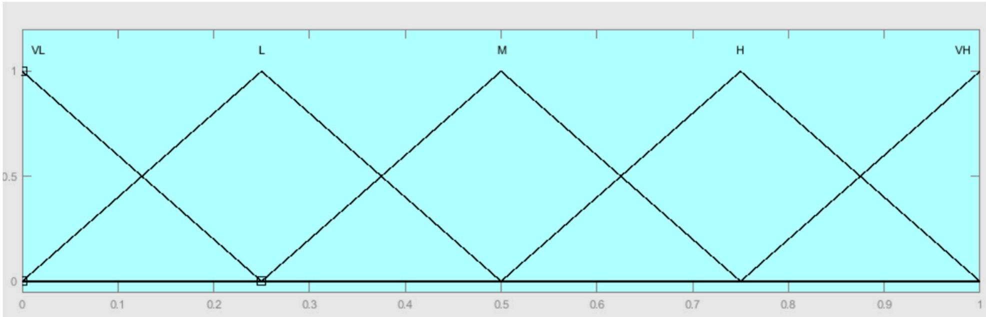

Figure 4. Output membership function.

- Fuzzy rules:

Inference is performed using if–then rules, which establish relationships between multiple input and output variables. As these rules are based on word descriptions rather than strict mathematical definitions, fuzzy logic can effectively define any relationship that can be described, using linguistic terms. Consequently, fuzzy logic enables the description and control of even nonlinear systems. The if–then rules establish connections between the conditions represented by input membership functions and the corresponding output membership functions. The "if" part of a fuzzy rule serves as the antecedent, specifying the membership function for each input variable. The "then" part of a fuzzy rule serves as the consequence, specifying the membership function for each output variable. For instance, the following example provides an illustrative representation of the 9 fuzzy rules employed for the design of the fuzzy structural (FIS3) block, which is answered by one of the experts.

1. If (soft factors is poor) and (hard factors is poor) then (structural is very low)
2. If (soft factors is poor) and (hard factors is average) then (structural is very low)
3. If (soft factors is poor) and (hard factors is good) then (structural is medium)
4. If (soft factors is average) and (hard factors is poor) then (structural is low)
5. If (soft factors is average) and (hard factors is average) then (structural is medium)
6. If (soft factors is average) and (hard factors is good) then (structural is high)
7. If (soft factors is good) and (hard factors is poor) then (structural is medium)
8. If (soft factors is good) and (hard factors is average) then (structural is high)
9. If (soft factors is good) and (hard factors is good) then (structural is very high)

- Defuzzification

The output of each fuzzified rule is fed into the FIS, and the resulting output is then subjected to the defuzzification process to obtain actual numerical results. There are several defuzzification techniques available, including the center of sums method (COS), center of gravity method (COG), centroid of area method (COA), bisector of area method (BOA), middle of maximum method (MOM), smallest of maximum method (SOM), and largest of maximum method (LOM), to name a few examples. In this study, the COA method was employed for the defuzzification process, due to the symmetrical nature of the triangular membership functions used in this research. For such cases, the COA method demonstrates superiority over other methods by providing a proper crisp value for the maximum membership function ($\mu = 1$) [37]. The COA method determines the center of gravity of the fuzzy set along the x-axis. If we were to consider the area as a plate with uniform thickness and density, the COA method represents the point along the x-axis where the fuzzy set would balance. An example calculation of the COA method is presented in Equation (2).

$$X_{COA} = \frac{\sum_{i=1}^{n} x_i \mu_i(x_i)}{\sum_{i=1}^{n} \mu_i(x_i)} \quad (2)$$

- Modified architecture of FIS engine

In this step, fuzzy rule sets for the FIS model are formulated based on expert knowledge. The number of fuzzy rules in each FIS model can be calculated using Equation (3).

$$N = M^V, \tag{3}$$

where:

N = number of fuzzy rules
M = number of membership functions (in this study, it is 3 {“poor” = (0, 0, 0.5), “average” = (0, 0.5, 1) and “good” = (0.5, 1, 1)})
V = number of input variables for every FIS engine/block

For instance, nine rules must be developed when M = 3 and V = 2. The number of rules for the same number of membership functions rises to 27; however, if V = 3, as a result, the rule count exponentially grows through the addition of other input variables for a given number of membership functions. [38]. The hierarchical FIS establishes a network of interconnected FISs. As mentioned, a critical issue with traditional FIS is rule explosion when additional parameters are added to the system. Rule explosion has two main drawbacks: it escalates the computational complexity of the system, and poses significant challenges in designing a large number of rules. In this research, we introduced the hierarchical FIS to address the problems associated with conventional fuzzy logic. The conventional fuzzy logic is depicted in Figure 5.

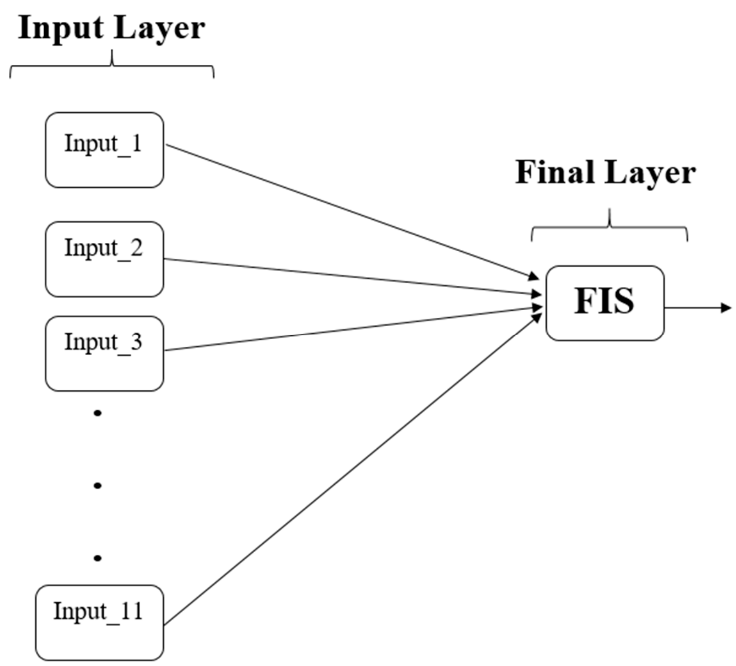

Figure 5. Traditional FIS.

The proposed model, referred to as the cohesive model, is illustrated in Figure 6. This model consists of four layers: an input layer, the first middle layer, the second middle layer, and the top-level layer. The input layer comprises eleven inputs, namely management structure, personality–job fit, in-service program, reward management, ergonomic design, work motivation, job satisfaction, personal skills, job security, organizational culture, and economic stability. The first middle layer consists of two FISs, namely FIS_1 and FIS_2. The second middle layer consists of three FISs, namely FIS_3, FIS_4, and FIS_5. FIS_1 takes inputs from management structure, personality–job fit, and in-service program, while FIS_2 takes inputs from reward management and ergonomic design. The outputs of FIS_1 and FIS_2 serve as inputs to FIS_3. FIS_4 takes inputs from work motivation, job satisfaction, and personal skills, while FIS_5 takes inputs from job security, organizational culture, and economic stability. The outputs of FIS_3, FIS_4, and FIS_5 are further used as inputs to FIS_6 in the top-level layer [39]. It is important to note that without designing a hierarchical FIS, we have $3^{11} = 59049$ rules in a traditional FIS. To address this issue, we defined and categorized factors based on a three-pronged model.

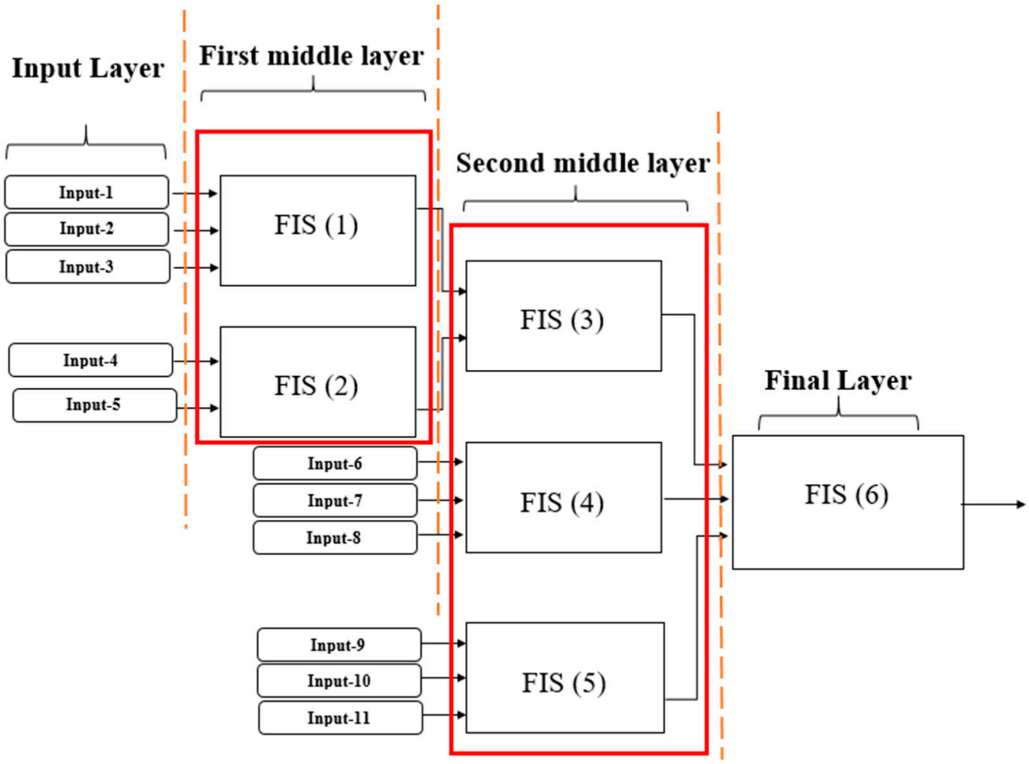

Figure 6. Cohesive FIS.

This reduction in rules leads to a decrease in model complexity, thereby improving interpretability. One of the key advantages of hierarchical fuzzy inference systems is the possibility to easily evolve the rule base. Instead of completely redesigning the rule base, a new layer can be added to update it. Additionally, unlike flat FISs, a hierarchical fuzzy inference system allows for the generation of different subsystem configurations to better adapt the system to various input variables. Despite achieving good classification results, the previous fuzzy rule base consisted of a large number of rules. This poses challenges in terms of manageability. In this study, we proposed a hierarchical approach to designing the fuzzy rule base to reduce the number of rules, while maintaining classification accuracy [40]. This approach was implemented in MATLAB 2019 or higher with the title "FIS tree". We distributed 11 factors of a traditional FIS into 6 factors across three initial branches: organizational (5 inputs), behavioral (3 inputs), and circumstantial (3 inputs). Furthermore, within the organizational factors, we subdivided them into two branches: soft factors (3 inputs) and hard factors (2 inputs). Consequently, in the proposed cohesive model, we incorporated two intermediate layers to minimize the number of rules to 126, as demonstrated by Equation (4) and depicted in Figure 6.

$$3^3 + 3^2 + 3^2 + 3^3 + 3^3 + 3^3 = 126 \tag{4}$$

4. Findings Case Study

The main objective of this research is to propose a novel methodology for assessing the performance of staff at the Fars Regional Electric Company. To detect, analyze, and organize the appraisal information within the company, a specific hierarchical FIS based on a triple-pronged approach was introduced. The evaluation of the appraisal information was carried out by six experts working in the productivity department. All of these experts possessed over 15 years of work experience, and had previously held managerial positions or key roles in their respective companies. Furthermore, they held bachelor's or master's degrees (Lisans or Karshenasi Arshad), respectively. As mentioned earlier, these experts provided answers to 126 fuzzy rule phrases to establish six FIS blocks. Subsequently, they assigned scores to the productivity of employees and the productivity of employee factors, considering the specific circumstances of the Fars Regional Electric Company. The results of this assessment are presented in Table 4.

Table 4. Initial evaluation of productivity of employees' factors.

Factors	1st Expert	2nd Expert	3rd Expert	4th Expert	5th Expert	6th Expert	Average of Scores
Management structure	0.45	0.55	0.40	0.45	0.65	0.55	0.5083
Personality–job fit	0.55	0.60	0.45	0.50	0.40	0.45	0.4910
In-service program	0.80	0.70	0.65	0.85	0.75	0.55	0.7160
Reward management	0.45	0.40	0.40	0.35	0.50	0.35	0.4083
Ergonomic design	0.60	0.55	0.60	0.45	0.55	0.45	0.5333
Work motivation	0.35	0.35	0.40	0.30	0.35	0.30	0.3416
Job satisfaction	0.50	0.55	0.45	0.55	0.60	0.55	0.5333
Personal skills	0.65	0.65	0.80	0.45	0.75	0.60	0.6500
Job security	0.50	0.60	0.70	0.35	0.60	0.40	0.5250
Organizational culture	0.40	0.60	0.35	0.55	0.50	0.60	0.5000
Economic stability	0.25	0.50	0.40	0.50	0.25	0.35	0.3583
Productivity of employees	0.55	0.50	0.40	0.55	0.60	0.50	0.5166

In this case, the implementation and design of the hierarchical FIS model were carried out using MATLAB version 2020. The sample data were carefully examined and selected for the present study. To exemplify the activation of rules based on the experts' evaluations from Table 4, the evaluators assigned scores to the productivity of employees' factors in the range of 0 to 100. The average scores for each factor were used as inputs, and the corresponding FIS block calculated the output based on the fuzzy rules and membership functions. For the first FIS block (soft factors), the scores for management structure, personality–job fit, and in-service program were 0.5083, 0.4910, and 0.7160, respectively. The result of FIS (1) was 0.6060. In the second FIS block (hard factors), the scores for reward management and ergonomic design were 0.4083 and 0.5333, respectively. The result of FIS (2) was 0.5420. The inputs for the third FIS block (structural factors) were the results of the first and second FIS blocks, which were 0.6060 and 0.5420, respectively. The result of FIS (3) was 0.4570. For the fourth FIS block (behavioral factors), the scores for work motivation, job satisfaction, and personal skills were 0.3416, 0.5333, and 0.6500, respectively. The result of FIS (4) was 0.5820. In the fifth FIS block (circumstantial factors), the scores for job security, organizational culture, and economic stability were 0.5250, 0.5000, and 0.3583, respectively. The result of FIS (5) was 0.3790. The inputs for the sixth FIS block (productivity of employee) were the results of the third, fourth, and fifth FIS blocks, which were 0.4570, 0.5820, and 0.3790, respectively. The final result was 0.4580, indicating that based on the experts' scores and the proposed model's calculation, the productivity of staff in the Fars Regional Electric Company was 45.8%. Figure 7 illustrates the calculation process of this multistage FIS block.

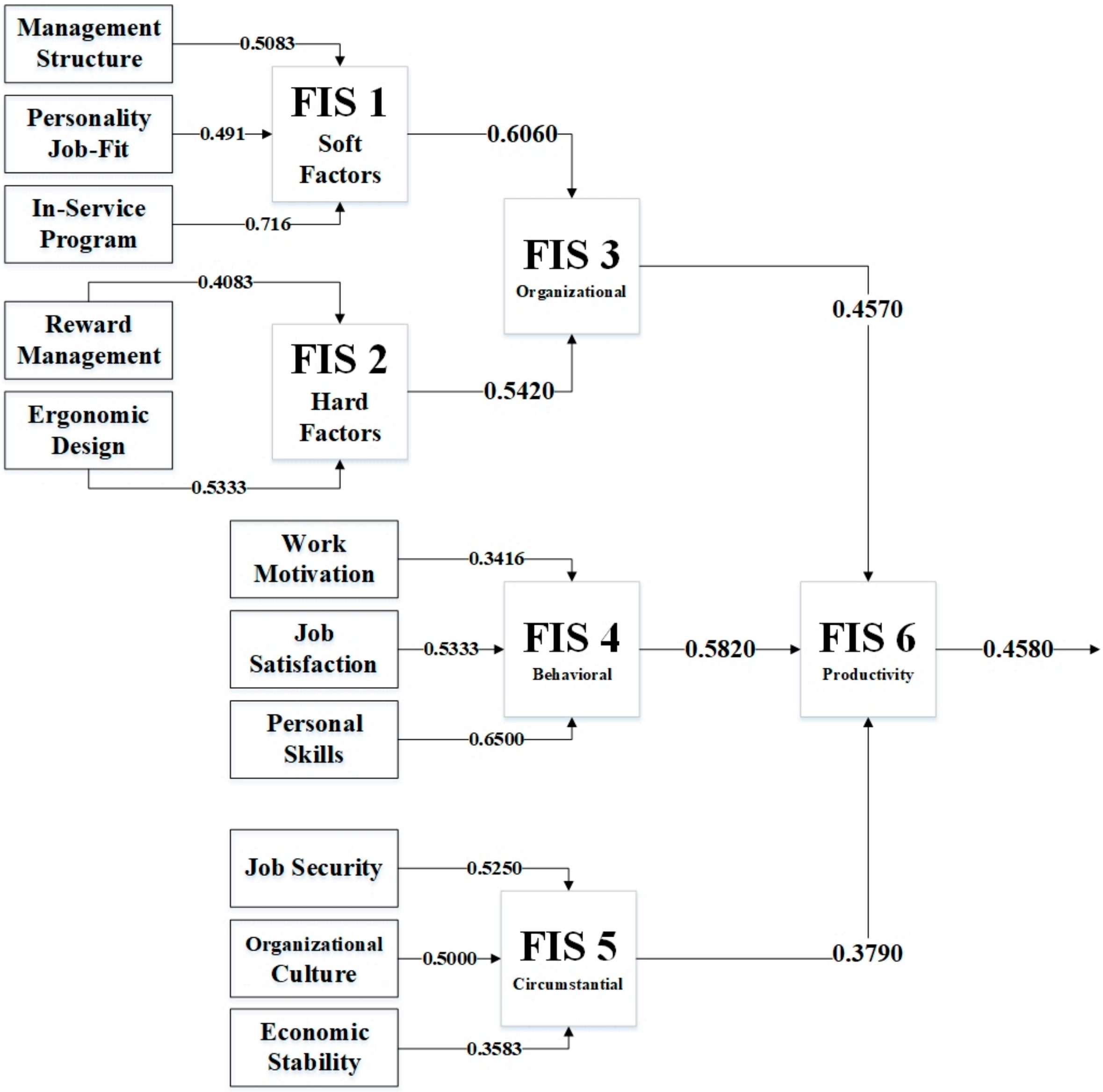

Figure 7. Experimental results.

Figure 8 depicts snapshots of the results obtained from the analysis conducted in MATLAB. Figure 8 showcases the rule viewer, which is a read-only tool displaying the complete fuzzy inference diagram, encompassing fuzzy implication, fuzzy aggregation, and defuzzification. On the other hand, the surface viewer, also a read-only tool, allows the representation of input and output values in 2-D or 3-D diagrams for selected cases. Figure 9 specifically demonstrates the 2-D and 3-D diagrams illustrating the productivity of employees' results in the Fars Regional Electric Company.

The research validity was assessed through two methods: content validity and structural validity. Content validity is established by consulting four academic experts who possessed valuable experience in authoring and translating books, as well as publishing scientific articles in relevant research fields. As for the structural validity, the evaluators who designed the fuzzy rules in advance were requested to score the productivity of employees (as shown in the last line of Table 4) based on the situation at the Fars Regional Electric Company. By comparing the mean squared error (MSE), root mean squared error (RMSE), and mean percentage error (MPE), as shown in Table 5, the scores and the model's outcomes were compared in this phase [41]. The errors validated by the model exhibited satisfactory validity, as they are less than half the distance between two output results $\{< \frac{0.25}{2} = 0.125\}$ [36].

In this formulation y_t represents the scores allocated by each expert to employee productivity [0.55, 0.50, 0.40, 0.55, 0.60, 0.50]; $\overline{y_t}$ represents the output of the FIS [0.458].

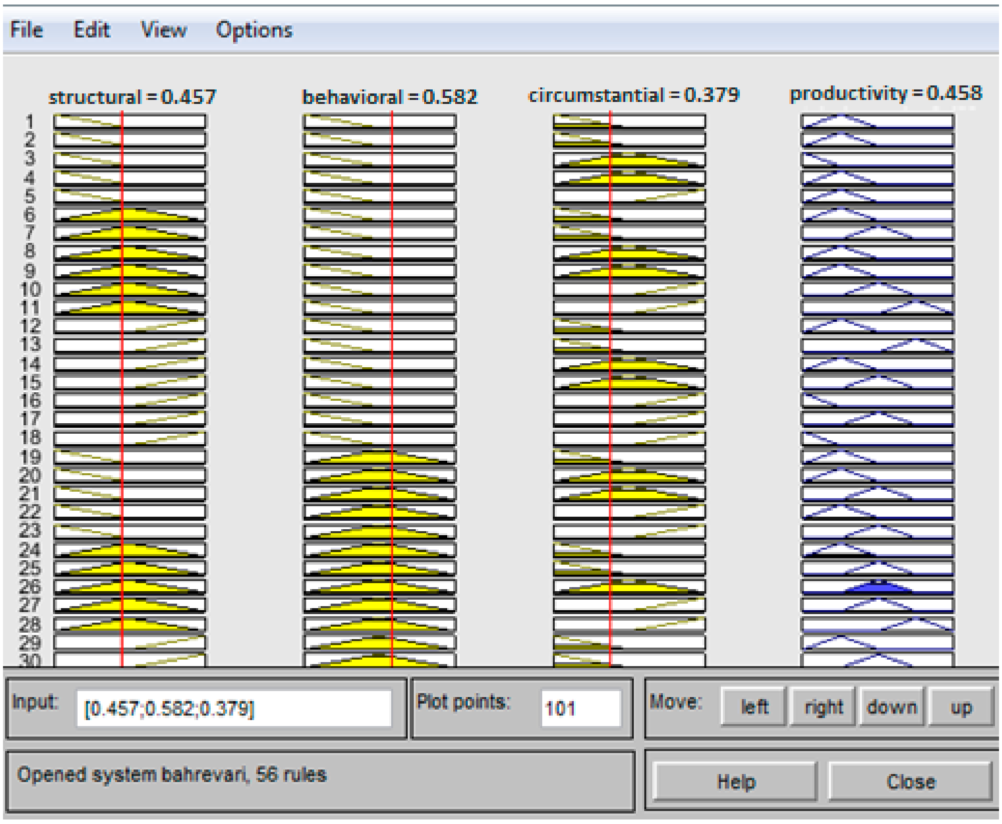

Figure 8. Rule viewer (view of input and output parameters).

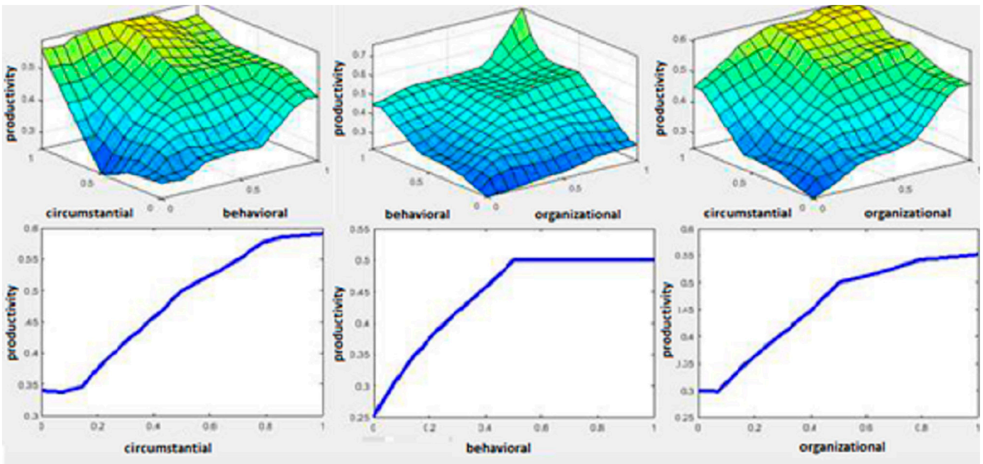

Figure 9. Surface viewer (view of input and output parameters) in 2-D and 3-D diagrams.

Table 5. Evaluation of validation errors.

Error	Formulation	Result
MSE (Mean Square Error)	$\sum_{t=1}^{n}(y_t - \overline{y_t})^2$	0.0073
RMSE (Root Mean Square Error)	$\sqrt{\frac{\sum_{t=1}^{n}(y_t-\overline{y_t})^2}{n}}$	0.0856
MPE (Mean Percentage Error)	$\frac{\sum_{t=1}^{n}\left[\frac{y_t-\overline{y_t}}{y_t}\right]}{n}$	0.0990

5. Discussion

Past studies have examined circumstantial factors, including organizational culture, economic stability, and job security, which have a significant relationship with employee performance. Regarding the relationship between organizational culture and employee performance, evidence suggests that adhocracy culture has the highest positive effect on performance, while the effect of hierarchy culture is negative [42]. Most studies indicate a positive and significant relationship between organizational culture and human resource productivity. Corporate spirituality offers a fresh viewpoint on corporate culture, and has been a hot issue among scholars studying management and organization in recent years. In the workplace, spirituality is a driving force that inspires and motivates people to continually look for meaning and purpose in their work, appreciate the real worth of their labor, and recognize the diversity of creation, nature, and personal belief systems that influence organizational culture [43]. Conversely, a toxic workplace environment negatively affects employee productivity [44]. Controlling circumstantial factors is not effortless, as organizations' regulation is limited to their environment and framework. However, organizations must consider responding appropriately to external changes, even if they are restricted to influencing or changing their circumstantial factors. Another factor in the circumstantial branch of employee performance is economic stability, which is associated with individual workers' behaviors. Markovits et al. (2017) investigated Greek employees' job attitudes and commitment during the economic crisis over a half-decade, in order to determine whether these were restored. Their findings revealed that the economic crisis reduced employees' job commitment, perspective, and well-being. This ongoing crisis further adversely affected all dimensions of job satisfaction, indicating that the intrinsic and extrinsic motivation of Greek employees suffered from the economic crisis, making it very difficult for them to adapt to such a situation [45]. Job security, which is part of social security, is another factor in the circumstantial prong. It is a crucial factor for success and development in businesses and companies, with a significant impact on productivity and performance. The goal of job security is to increase employees' reassurance about their future careers, and alleviate concerns for the future [46]. Findings from an American study on job security demonstrate that concerns about job loss not only negatively affect employees' performance, but also impacts their health, leading to increased blood pressure and potential diseases that may shorten an their lives [47]. Another significant aspect of productivity is structural factors, with in-service programs among the soft factors and reward management among the hard factors being particularly important. In-service training is a strategy through which organizations aim to enhance efficiency, considering the remarkable developments in science and technology that have influenced various aspects of administration and organization, highlighting the necessity of educating and updating human resources [48]. Productivity encompasses any efforts to improve the lives of individuals and society, as well as their philosophical ideologies. Therefore, training employees can bring validity to organizations and positively impact productivity and job satisfaction [49]. Reward management is essential for organizations, not only for increasing employee productivity but also for managing their performance. The reward system, directly and indirectly, aligns with the vision and mission of the organization, and significantly impacts employee productivity by motivating workers; it serves as a means to achieve high levels of performance [50]. Reward management can be categorized into salary, bonuses, appreciation, and medical benefits. All of these aspects of the reward system exhibit a positive correlation with employee performance, indicating that both financial and non-financial rewards significantly impact staff productivity [51]. The study's findings demonstrate that while investing in behavioral factors initially enhances staff productivity, it ultimately does not have a significant influence on the output of the productivity of employees. Among the behavioral factors, personal skills and job satisfaction exert a greater effect on employee performance. Competency management, an operational human resource management tool, shows a strong correlation with personality–fit, and aims to optimize employee performance. Competence is developed by individuals in specific professional situations, and it evolves. It appears that competence is a means to increase employees' capacity and develop their skills to fulfill their missions. Enhancing employee skills not only improves company performance, but also contributes to the company's values. Competence encompasses behavior, experience, and the ability to carry out professional activities in collaboration with the organization and society, utilizing staff knowledge and know-how within a given context [52]. Personal skills, such as conscientiousness, directly impact employee performance by fostering traits such as responsibility, organization, and discipline. Another important personal skill, extraversion, serves as a positive and significant predictor of productivity, indicating that outgoing, social, and communicative employees tend to perform better than those who prefer to remain introverted [53]. Job satisfaction is defined as an individual's positive and measurable evaluation of their working conditions. It is widely acknowledged that job satisfaction is a key determinant of employee performance, as happier workers tend to be more productive. Job satisfaction is closely linked to working conditions, emphasizing the need for organizations to provide an environment that enables employees to work freely, without constraints that hinder them from reaching their full potential. Additionally, the nature of the job itself exhibits a positive correlation with job satisfaction [54]. Job satisfaction also contributes to increased employee productivity through factors such as pay, promotion opportunities, job autonomy, and positive relationships with co-workers and supervisors [55].

6. Conclusions

The objective of the present investigation was to offer an alternative approach for assessing employee productivity through the utilization of an FIS. The feasibility of the suggested approach was ascertained via a case study conducted in collaboration with the Fars Regional Electric Company. According to the feasibility study, the proposed approach utilizing an FIS possesses the capability to precisely assess the productivity of employees. Thus, this study presents a new approach to exploring the concept of employee productivity. The research reveals the importance of productivity to individuals, organizations, and the overall environmental context. The results illustrate that circumstantial issues can have a specific impact on the productivity of an employee's growth. Through the utilization of an FIS, the intricacies and uncertainties inherent in performance evaluation were effectively captured in a manner that was characterized by its adaptability and flexibility. In contrast to traditional methods of performance assessment, the utilization of linguistic variables and fuzzy rules in the FIS model facilitated a more comprehensive and intricate appraisal.

This study presented a distinct advantage utilizing a unique approach. During the interview process, evaluators' responses to questions were based on their assessments, and the fuzzy inference system (FIS) effectively simulated their evaluations. In our study, we implemented an innovative methodology that classified experts' assessments using an FIS. In contrast to the methodologies employed in the aforementioned studies, our novel approach inherently assigned weights to the questions based on the evaluators' responses.

Furthermore, we tackled the challenge of rule explosion by designing a hierarchical FIS. While some similar studies focused on examining only one factor using an FIS, our study simultaneously examined 11 factors within an organization and prioritized them accordingly. This approach allowed us to address the complexity and provide comprehensive insights.

The practical significance of this study was enhanced by the involvement of the Fars Regional Electric Company. The practical application of the proposed methodology was demonstrated through its implementation in a real-life business scenario, showcasing its utility and effectiveness. The technique was validated through a collaborative effort between researchers and professionals in the field, who engaged in a reciprocal exchange of information. In the end, the results of this investigation demonstrate that FISs exhibit potential as a feasible approach for assessing employee performance. The favorable outcomes of the feasibility assessment demonstrate the efficacy of FISs in real-world contexts, such as employment interviews. The findings of this research provide evidence for further exploration and refinement of performance evaluation techniques utilizing FISs, with the aim of improving the accuracy and impartiality of employee assessments within organizational settings.

7. Study Limitations

The limitations of this research encompass several aspects. Firstly, it should be noted that the geographical scope of this study was restricted. Furthermore, each questionnaire was considered a constraint due to its reliance on expert interviews, which solely examined individuals' perspectives rather than objective reality. Hence, this aspect can be perceived as a limitation in itself. Moreover, other limitations observed in this study include the intellectual capacity, level of interest, scientific and specialized abilities of the respondents, as well as the psychological states of the experts during the question–answer process, which were beyond the researchers' control.

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