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Neuro-Fuzzy Performance Evaluation System: A Comprehensive Approach for Team Member Assessment

Ms. Ramandeep Kaur

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A B S T R A C T

In this research paper, an intelligent system based on neuro-fuzzy principles has been developed to assess the performance of team members. The system incorporates five distinct inputs and produces a single output. The inputs include results from an engagement survey, employee satisfaction levels, special project costs, the number of days active in the last 30 days, and the frequency of absences. The output, in turn, represents the performance score of a team member. Each input and output is characterized by membership functions, with three membership functions assigned to each input and four to the output. These membership functions play a crucial role in capturing the nuances and complexities associated with the performance evaluation process. In the proposed work section of the paper, specific details regarding the membership functions are discussed, shedding light on their design and significance within the neuro-fuzzy framework. The authors delve into the rationale behind the chosen membership functions, demonstrating their relevance in capturing the diverse range of input variables and providing insights into the resulting performance scores. The implementation of the entire project is carried out using MATLAB, a powerful computational tool widely employed in scientific and engineering applications. The utilization of MATLAB ensures a robust and efficient execution of the neuro-fuzzy system. The dataset used in this research was sourced from Kaggle, a popular platform for machine learning and data science. The choice of Kaggle as the data source adds credibility to the study, as the platform is renowned for hosting high-quality datasets and fostering collaboration among data scientists. Notably, the proposed technology exhibits an impressive accuracy rating of 92%, showcasing its efficacy in accurately assessing team member performance. This high accuracy level underscores the potential practical application and reliability of the neuro-fuzzy-based intelligent system in real-world scenarios involving performance evaluation in team settings.

Keywords: MATLAB, Fuzzy Logic, Machine Learning, Neuro-fuzzy-based Intelligent System

INTRODUCTION

Fuzzy logic serves as a methodology for constructing models that leverage real data within a structured range, preserving key elements of classical reasoning. Particularly recommended for handling imprecise information and facilitating reasoned decisions in uncertain environments, fuzzy logic stands out as a valuable data processing technology. The construction of a fuzzy expert system involves three essential steps.

In the initial phase, non-fuzzy sets undergo fuzzification, transforming them into fuzzy sets. Fuzzification is the term denoting this conversion. The second step involves translating the input fuzzy set into the corresponding output fuzzy set. Finally, in the third step, the fuzzy set values are converted into concrete values. The Mamdani fuzzy system is widely recognized for encapsulating expert knowledge and representing information in a more discerning manner. Employing the defuzzification method, the Mamdani fuzzy system refines fuzzy results.

Due to its perceptual rule base environment, the Mamdani fuzzy system finds common use in decision support applications during the system design phase. It is notable for its rigidity in the design process. On the other hand, the Sugeno fuzzy system calculates the crisp output using the weighted average method, eliminating the need for a defuzzification procedure. Consequently, the Sugeno fuzzy system skips the defuzzification phase altogether and lacks output membership functions.

The Sugeno approach, known for its computational capabilities, excels in adaptive and optimization procedures, making it particularly effective in addressing direct issues. The ability of optimization and adaptive methods to alter membership functions ensures that the fuzzy expert system optimally processes data. Combining fuzzy logic and neural networks, the neuro-fuzzy system represents an adaptive approach, offering enhanced efficiency. This adaptive neuro-fuzzy expert system presents a promising solution approach.

LITERATURE SURVEY

Various research studies have explored the application of fuzzy logic and related methodologies in developing intelligent systems for medical diagnoses and performance evaluations. Rama Devi. E. and Dr. Nagaveni. N. (2010) focused on diabetic nephropathy detection, employing a fuzzy knowledge-based system with triangular membership functions. Input parameters such as hyperglycemia, insulin, ketones, lipids, obesity, blood pressure, and protein to creatinine ratio were used to predict stages of renal disorder. This system, validated with MATLAB, demonstrated accuracy and robustness, offering a tool for optimal control of high-risk factors.

Similarly, Mohammed Abbas Kadhim et al. (2011) introduced an intelligent system for back pain disease diagnosis, utilizing fuzzy logic. Their model considered parameters like body mass index, age, and gender, achieving an accuracy rate of 90%. X.Y. Djam and Y. H. Kimbi (2011) delved into hypertension diagnosis using fuzzy logic, reaching an 85% accuracy rate, with the Mamdani fuzzy system and centroid method for defuzzification.

M.F. Ganji and M.S. Abadeh (2011) integrated ant colony optimization and fuzzy systems in the FCS-ANTMINER for detecting diabetes, boasting an accuracy of 84.24%. Azian Azamimi Abdullah et al. (2011) developed a fuzzy medical expert system for hypertension risk diagnosis, catering to patients aged 20 to 40 years, with a focus on age, BMI, blood pressure, and heart rate. Vishali Bhandari and Rajeev Kumar (2015) applied both Mamdani-type and Sugeno-type fuzzy expert systems for diabetes diagnosis, demonstrating the superiority of Sugeno systems.

Moving beyond medical applications, Arshdeep Kaur and Amrit Kaur (2012) explored fuzzy inference systems for air conditioning, comparing Mamdani and Sugeno types. Moreover, they introduced fuzzy and neuro-fuzzy systems for air conditioning, with the latter proving superior.

In a different domain, M. Kalpana (2011) highlighted the synergy of fuzzy logic and expert systems for efficient diabetes diagnosis. Arshdeep Kaur and Amrit Kaur (2012) further explored fuzzy systems and neuro-fuzzy systems for air conditioning, demonstrating the latter's superiority.

Additionally, Qeethara Kadhim and AL-Shayea (2011) applied artificial neural networks to classify patients with acute nephritis and heart disease, achieving high accuracy rates of 99% and 95%, respectively. W. Luangruangrong et al. (2012) focused on diagnosing risk factors of type 2 diabetes using backpropagation neural networks, reaching an accuracy of 84%.

Furthermore, Rupinder Kaur and Amrit Kaur (2014) emphasized the need for an intelligent medical expert system to diagnose hypertension, with their fuzzy expert system considering parameters like age, BMI, blood pressure, heart rate, diabetes, physical activity, and genetics.

Lastly, Ramiro Meza-Palacios et al. (2016) developed a fuzzy expert system for assessing nephropathy control in type 2 diabetes patients, achieving a success rate of up to 93.33%. Overall, these studies showcase the versatility and efficacy of fuzzy logic and related methodologies in diverse domains, offering valuable insights for medical diagnoses and performance evaluations.

PROBLEM DESCRIPTION

A performance evaluation serves as an assessment of an individual's job performance and responsibilities. Ideally, it should act as a platform for both the employee and the supervisor to identify and discuss areas where performance enhancements are possible. Moreover, it offers an opportunity to clarify expectations between the employee and manager. Poorly managed performance evaluations can have detrimental effects on a corporation in various ways. An employee who performs well but feels unfairly treated may experience a loss of self-esteem, fostering animosity towards management and resulting in lower engagement and performance.

Providing negative feedback without supporting data or facts can be perilous, as employees who perceive unfair evaluations may resort to legal action against the company. Biased reviews are also more likely when managers lack data and metrics for evaluation. Intelligent systems are crucial in addressing these challenges. Simple rule-based systems are insufficient, as they cannot accurately determine the likelihood of an employee's performance rating being accurate. Even if one parameter is missing in simple rule-based systems, the employee may be incorrectly evaluated. Such systems rely on the user affirming the values of evaluation parameters through a yes or no response. However, they lack the capability to calculate the likelihood of the evaluation's accuracy.

This is where fuzzy logic becomes essential. Fuzzy logic allows the system to calculate the likelihood that the evaluation aligns closely with reality. However, a drawback of fuzzy intelligent systems is the manual selection and design of membership functions and fuzzy rules. This presents a critical challenge in fuzzy modeling. To overcome this limitation, this study employs a hybrid model – a neural fuzzy inference system – for employee performance evaluation. Unlike traditional fuzzy systems, the rules and membership functions in this hybrid model are generated automatically, offering a more efficient and unbiased approach to performance assessment.

PROPOSED WORK

The proposed intelligent system, grounded in the neuro-fuzzy approach, incorporates five inputs. These inputs are as follows:

1. Engagement Survey

2. Employee Satisfaction

3. Special Projects Count

4. Days Late in the Last 30 Days

5. Absence

Engagement Survey

The input variable "Engagement Survey" is characterized by three distinct membership functions, delineating the range of possible survey responses. The three membership functions associated with this input are categorized as follows: "Contented," "Satisfied," and "Unsatisfied." These membership functions, depicted in Figure 1, visually represent the fuzzy boundaries that define each level of engagement.

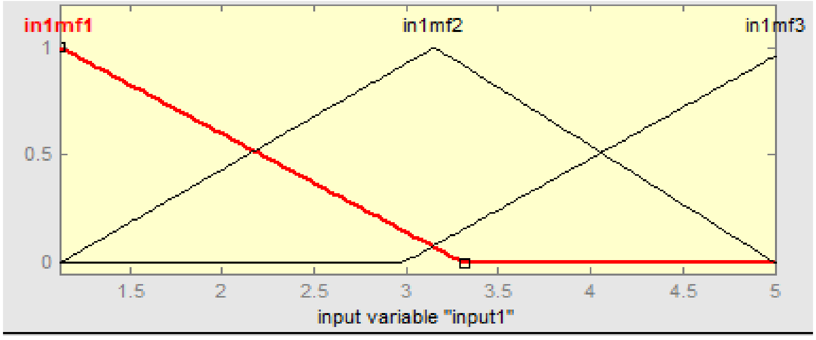

Figure 1: Input membership functions of Engagement survey.

Figure 1 illustrates the input membership functions of the Engagement Survey, each denoted as follows:

- **In1mf1:** Input 1, Membership Function 1 (Contented)

- **In1mf2:** Input 1, Membership Function 2 (Satisfied)

- **In1mf3:** Input 1, Membership Function 3 (Unsatisfied)

These membership functions play a crucial role in capturing the nuances and gradations of engagement levels reported in the survey. They provide a structured representation that facilitates the subsequent fuzzy logic-based processing within the intelligent system, allowing for a more nuanced and context-aware evaluation of team members' engagement levels.

Employee Satisfaction

The input variable "Employee Satisfaction" is characterized by three distinct membership functions, representing varying levels of satisfaction: "Good," "Average," and "Poor." These membership functions, depicted in Figure 2, visually illustrate the fuzzy boundaries associated with each level of employee satisfaction.

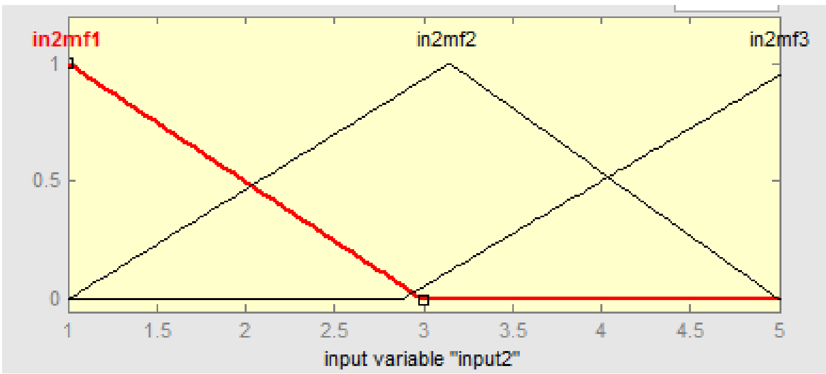

Figure 2: Satisfaction

Figure 2 provides a visual representation of the input membership functions for Employee Satisfaction, identified as follows:

- **In2mf1:** Input 2, Membership Function 1 (Good)

- **In2mf2:** Input 2, Membership Function 2 (Average)

- **In2mf3:** Input 2, Membership Function 3 (Poor)

These membership functions serve as a structured framework, facilitating the incorporation of subjective employee satisfaction data into the neuro-fuzzy-based intelligent system. By categorizing satisfaction levels in a fuzzy manner, the system can better interpret and analyze the nuanced responses from team members, contributing to a more comprehensive performance evaluation.

Special projects count

The input parameter "Special Projects Count" is characterized by three distinct membership functions, delineating the range of project involvement: "Poor," "Normal," and "Outstanding." These membership functions, illustrated in Figure 3, visually represent the fuzzy boundaries that define different levels of project engagement.

In Figure 3, the input membership functions for Special Projects Count are identified as follows:

- **In3mf1:** Input 3, Membership Function 1 (Poor)

- **In3mf2:** Input 3, Membership Function 2 (Normal)

- **In3mf3:** Input 3, Membership Function 3 (Outstanding)

These membership functions provide a nuanced representation of team members' involvement in special projects, categorizing their contributions in a fuzzy manner. By employing these fuzzy boundaries, the neuro-fuzzy-based intelligent system can better capture the diverse degrees of project performance, contributing to a more refined and context-aware performance evaluation. The visual representation in Figure 3 aids in understanding how the system interprets and processes the Special Projects Count input, enhancing the transparency of the evaluation methodology.

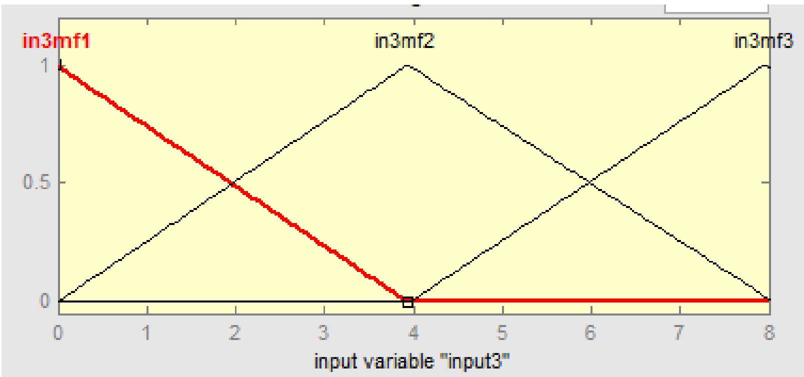

Figure 3: Input membership function for special projects count

Days late last 30

The input variable" Days Late Last 30" is characterized by three distinct class functions, representing different degrees of punctuality" High,"" Moderate," and" Low." These class functions, visually depicted in Figure 4, outline the fuzzy boundaries associated with the punctuality situations of team members.

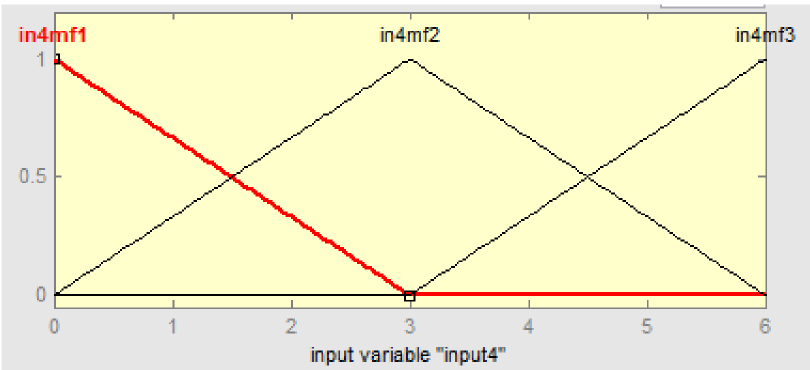

Figure 4: input membership functions for Days late last 30

Figure 4 presents a graphical representation of the input membership functions for Days Late Last 30, specifically labeled as:

- **In4mf1:** Input 4, Membership Function 1 (High)

- **In4mf2:** Input 4, Membership Function 2 (Moderate)

- **In4mf3:** Input 4, Membership Function 3 (Low)

These membership functions serve as a structured framework for interpreting the timeliness of team members' actions within the last 30 days. The fuzzy categorization allows the neuro-fuzzy-based intelligent system to capture the nuanced variations in timeliness behaviors, contributing to a more comprehensive and context-aware performance evaluation. Figure 4 aids in visualizing how the system interprets and processes the Days Late Last 30 input, enhancing the clarity and understanding of the evaluation methodology.

Absence

The input parameter "Absence" is characterized by three distinct membership functions, representing different levels of absence: "High," "Average," and "Low." These membership functions, visually presented in Figure 5, delineate the fuzzy boundaries associated with varying degrees of absenteeism.

In Figure 5, the input membership functions for Absence are explicitly labeled as follows:

- **In5mf1:** Input 5, Membership Function 1 (High)

- **In5mf2:** Input 5, Membership Function 2 (Average)

- **In5mf3:** Input 5, Membership Function 3 (Low)

This visual representation serves as a structured guide for interpreting the degree of absenteeism exhibited by team members. The fuzzy categorization enables the neuro-fuzzy-based intelligent system to effectively capture nuanced variations in absenteeism levels, contributing to a more refined and context-aware performance evaluation. Figure 5 provides a clear visualization of how the system interprets and processes the Absence input, enhancing transparency and facilitating a better understanding of the evaluation methodology.

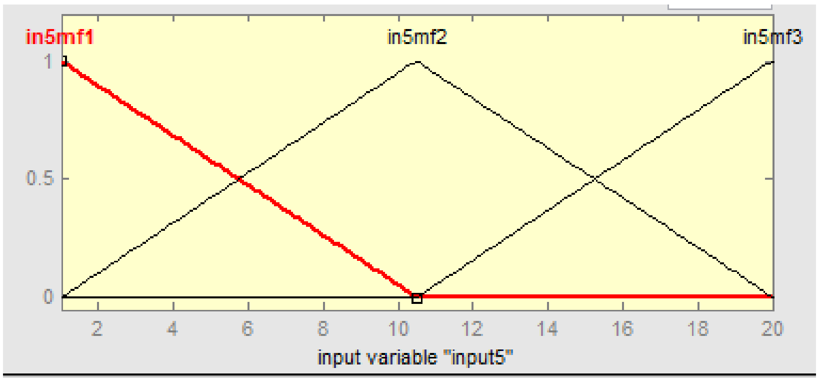

Figure 5 represents the input membership functions for absence

The output generated by the proposed system is the performance score, and it is categorized by four distinct membership functions, each representing a different level of performance evaluation:

a) **Needs Improvement**

b) **Performance Improvement Plan (PIP)**

c) **Fully Meets**

d) **Exceeds**

These membership functions provide a structured framework for classifying and interpreting the overall performance of team members. Each membership function corresponds to a specific level of achievement, ranging from areas that require enhancement ("Needs Improvement") to outstanding performance that surpasses expectations ("Exceeds"). The inclusion of these membership functions allows the neuro-fuzzy-based intelligent system to deliver a nuanced and context-aware assessment of individual performance. This categorization serves as a valuable tool for both employees and supervisors, facilitating clear communication and targeted improvement efforts based on the identified performance level.

The structure of the system, Rules, Rule viewer, Surface viewer, ANFIS structure, Training error are shown in figure 6, 7,8 and 9 respectively.

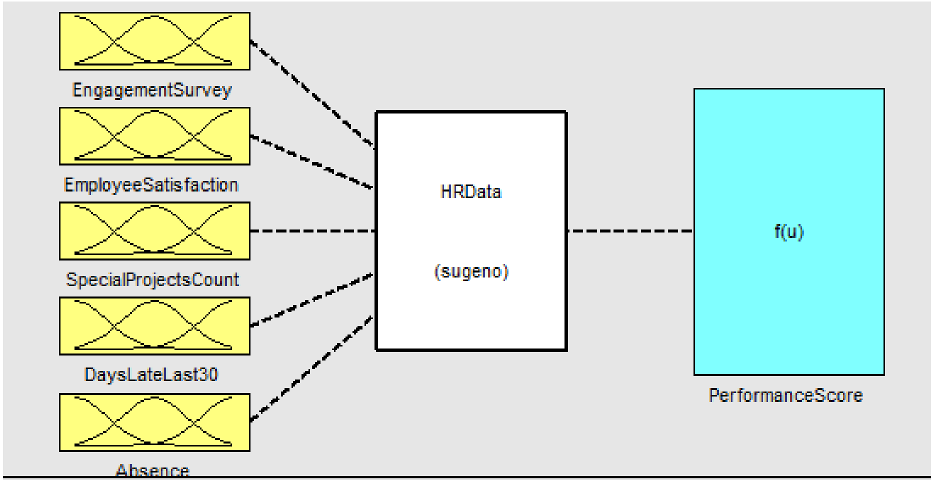

Figure 6: The structure of the proposed system.

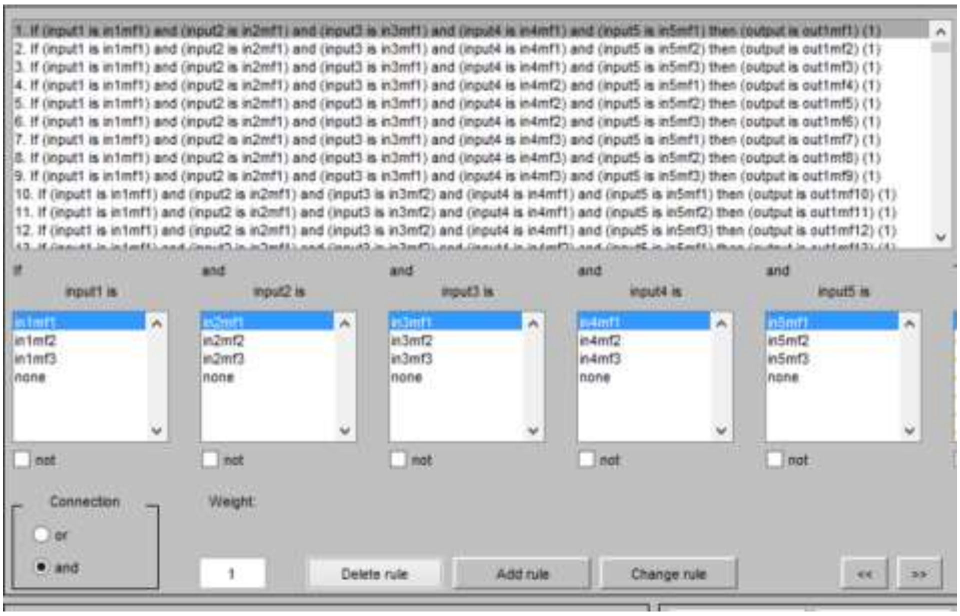

Figure 7: Rules

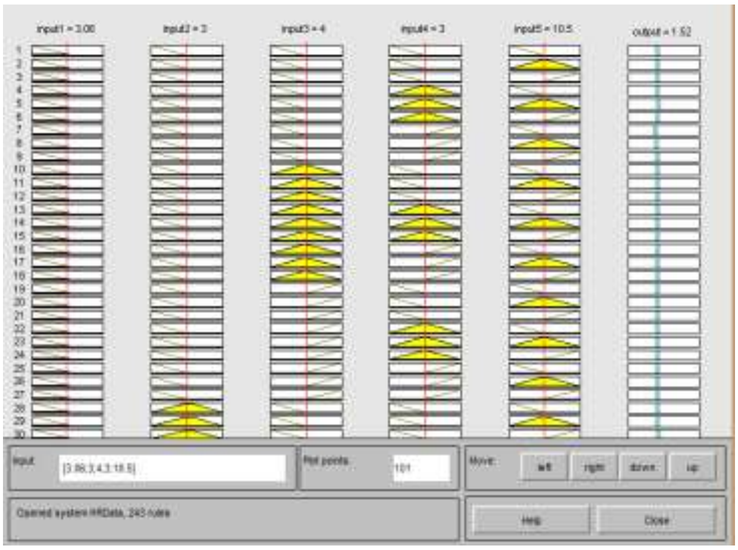

Figure 8: Rule Viewer

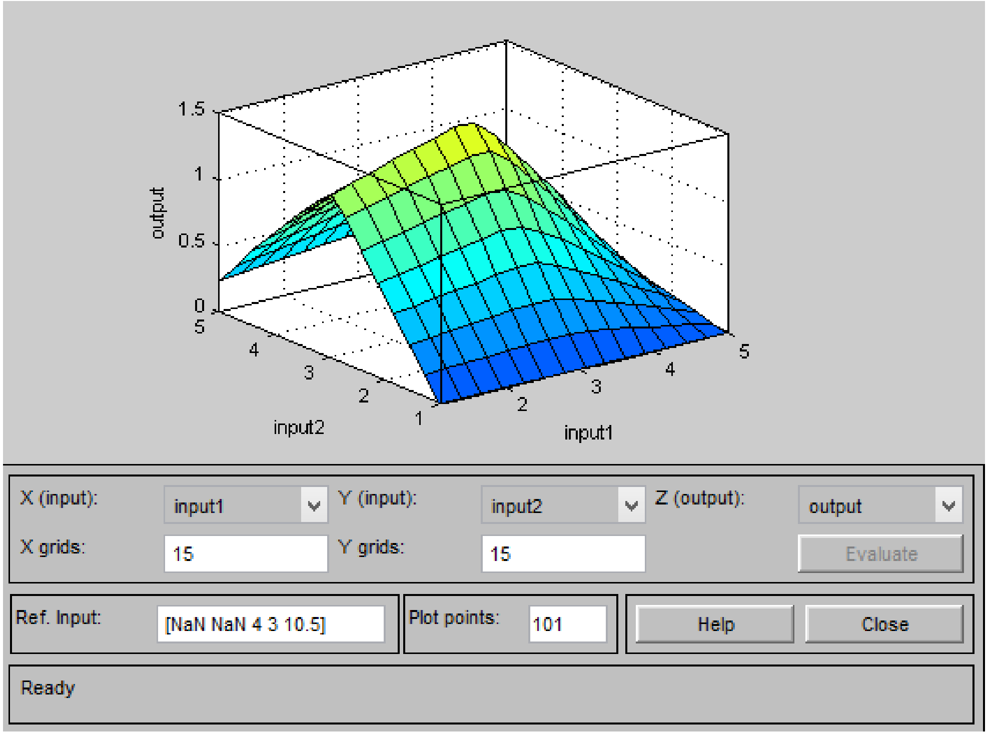

Figure 9: Surface Viewer

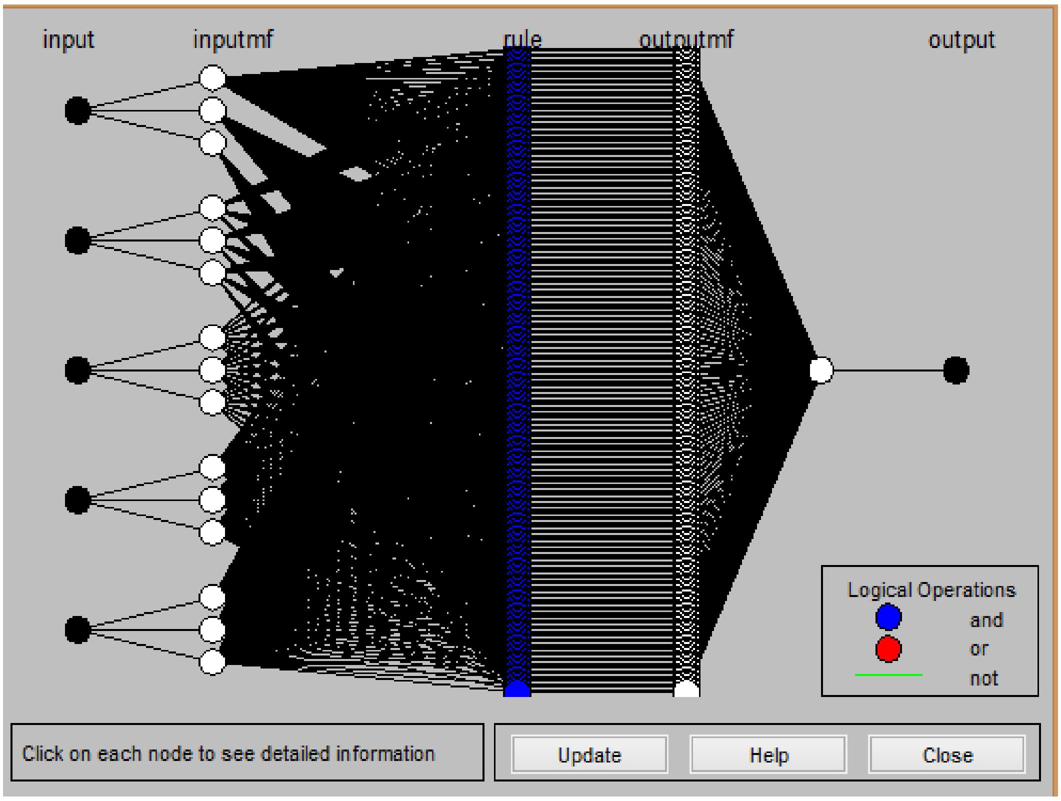

Figure 10: ANFIS Structure

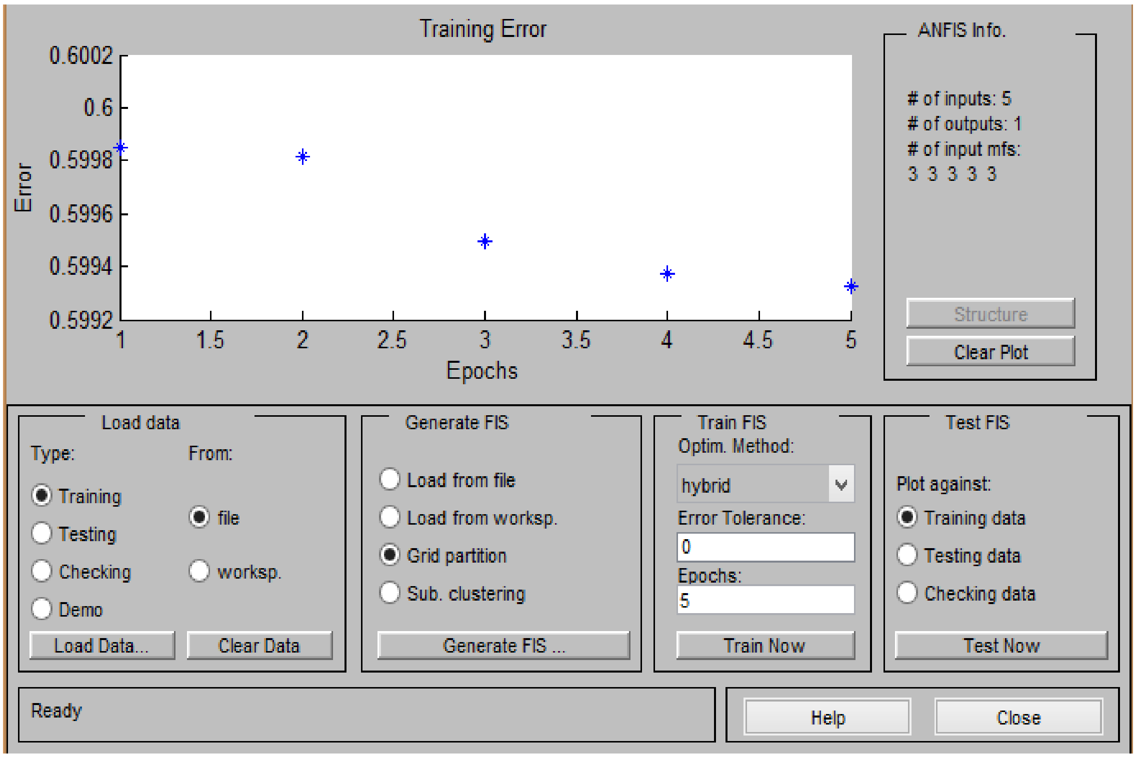

Figure 11: Training Error

RESULTS

The dataset utilized in this research was sourced from the Kaggle website and subsequently divided into two distinct sets: a training dataset and a testing dataset. Specifically, 75% of the total dataset was allocated to the training set, while the remaining 25% constituted the testing set. The training process involved the system being trained on 75% of the dataset, with the subsequent application of the remaining portion, the testing dataset, to evaluate the suggested system.

During the testing phase, the system's inputs were provided, and the corresponding outputs were recorded. These outputs were then compared to the actual outputs, enabling the calculation of key performance metrics such as the true positive rate, false positive rate, true negative rate, and false negative rate. Subsequently, the accuracy performance parameter was determined using these metrics, revealing an accuracy rate of 92 percent.

This comprehensive approach to dataset utilization, training, and testing ensures a robust evaluation of the suggested system's performance. The accuracy parameter, derived from the comparison of system-generated outputs to actual outcomes, serves as a quantitative measure of the system's effectiveness in assessing team member performance.

CONCLUSION AND FUTURE SCOPE

In conclusion, the developed system stands as a highly advantageous tool for the comprehensive performance evaluation of personnel within the company, as evidenced by the findings of this research. The system presents significant benefits to employers, offering a sophisticated method for assessing and analyzing the performance of team members. It is important to note that the implementation of this system requires access to a computer or machine equipped with MATLAB software, making it a viable and accessible solution for organizations invested in optimizing performance management.

Looking ahead, there exists substantial potential for enhancing the system's capabilities and outcomes. One avenue for improvement involves the incorporation of new inputs and outputs to further refine and expand the scope of the performance evaluation. The flexibility of the proposed system allows for seamless integration of additional variables, providing organizations with the opportunity to tailor the evaluation process to specific needs and evolving requirements.

Furthermore, to augment the system's efficacy, continuous training with an expanded dataset is recommended. The incorporation of more diverse and extensive datasets during the training phase can significantly contribute to the system's adaptability and accuracy. This continuous learning approach ensures that the system remains attuned to evolving patterns and nuances in team member performance, thereby reinforcing its utility as a dynamic and responsive tool for performance assessment.

In essence, the proposed system not only addresses current performance evaluation needs but also lays the foundation for future advancements and refinements, positioning it as a valuable asset in the ongoing pursuit of optimizing workforce management strategies within the organization.

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