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Validation of the Talent-Oriented Organization Model in Social Security Based on Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract

In today's complex and competitive world, organizations, particularly social security institutions, require innovative approaches for talent management and the utilization of advanced technologies to keep pace with dynamic changes and evolving workplace demands. This study aims to design a talent-oriented organizational model for social security using Adaptive Neuro-Fuzzy Inference System (ANFIS) methods. Talent management, as one of the most critical challenges faced by organizations, demands novel and efficient strategies to identify, develop, and retain human talent by leveraging advanced technologies. In this research, a comprehensive literature review and analysis of the current needs in social security organizations were conducted to identify and categorize the key factors influencing talent management. Subsequently, an adaptive learning model utilizing neuro-fuzzy networks was developed to identify effective patterns in talent management based on real-world data. The findings of this study demonstrate that integrating artificial intelligence techniques with human resource management processes can enhance the accuracy and efficiency of organizational decision-making. This enables social security organizations to operate with greater flexibility and responsiveness to environmental changes. One of the innovative aspects of this research is the development of a decision support system based on ANFIS, which uses the organization's historical data to provide optimization recommendations for talent identification and development. This study offers effective solutions not only for social security organizations but also for other industries and organizations, contributing to better talent management and, consequently, improved organizational productivity and efficiency.

Keywords: Talent-Oriented Organization, Social Security, Adaptive Neuro-Fuzzy Inference System (ANFIS)

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1- Introduction

With rapid advancements in various scientific and technological domains, organizations are compelled to seek novel strategies to enhance their performance in today's dynamic and complex environments. One such strategy is the talent-oriented approach, recognized as a key tool for optimizing human resource management processes. Organizational behavior and talent management significantly influence an organization's performance and effectiveness. The ways organizations perceive and manage talent are continually challenged as globalization, digitalization, and technological advancements disrupt traditional definitions of work, workplace, and workforce (Cascio & Aguinis, 2019; Klaus, 2019).

One notable shift is in the roles organizations and employees play in workplace relationships, altering expectations regarding psychological contracts and careers (Cascio & Aguinis, 2019). Establishing effective talent pipelines remains a long-standing challenge for multinational corporations (Kazikco & Bedraou, 2016; Schaller et al., 2011; Salian et al., 2010). CEOs regularly identify existing skill and capability shortages as major threats to growth prospects (Collings et al., 2019). For example, a global HR professionals survey revealed that 40% of respondents faced challenges staffing global teams, and 75% identified foreign workers as key to innovation and growth in their organizations (Society for Human Resource Management, 2024).

Compared to domestic companies, multinationals benefit from accessing broader global talent pools through geographically distributed structures. However, the extent to which multinationals engage in global talent mobility varies. Those with integrated global operations tend to exhibit higher levels of mobility compared to those with relatively localized and independent operations (Marwah et al., 2024). Employees in the former often transfer across organizational units to facilitate control, coordination, and knowledge sharing, while those in the latter primarily work locally (Harzing, 2020).

Traditionally, many multinationals relied on so-called parent-country nationals for extended expatriate assignments. However, as globalization deepens, global supply chains grow more complex, and technology transforms work methodologies, the nature of global mobility is also evolving. Transfers can originate from any organizational unit and occur in various forms, including virtual global mobility, where employees engage in cross-border tasks without physical relocation. Careers have likewise evolved, becoming increasingly self-directed, while psychological contracts have adapted to reflect organizational volatility, ambiguity, and uncertainty (Meese, 2018).

Over time, the role organizations play in career management has shifted as careers become boundaryless and independent of traditional organizational structures (Verenick & Castel, 2019). Consequently, conventional talent management practices appear to conflict with emerging career trends and the evolving nature of organizational work (Crowley-Henry et al., 2019; Verenick & Kustal, 2019).

In today's fast-paced and dynamic world, the success and efficiency of organizations increasingly depend on their ability to identify, attract, develop, and retain human talent. Social security organizations, tasked with providing essential services to citizens, face multidimensional challenges, many of which relate to effective human resource management. However, traditional management structures are often insufficiently flexible or adaptive to meet new organizational demands.

Organizational talent management in social security systems requires a comprehensive and innovative approach to simultaneously identify and optimize individual potential while fostering organizational growth opportunities. Advanced technologies, such as Adaptive Neuro-Fuzzy Inference Systems (ANFIS), offer promising solutions. Combining the adaptability and flexibility of neural networks with fuzzy logic, these techniques can model complex systems like managerial frameworks and human resources.

This research seeks to answer how modern adaptive technologies can help design a model for talent-oriented social security organizations. The goal is to align organizational strategies with talent management to enhance productivity and overall efficiency while improving the responsiveness and adaptability of social security organizations to environmental changes and emerging societal needs. Such a model should ensure the sustainability of social services through talent cultivation and retention.

For successful talent management and organizational success, the complexity of careers must be integrated into talent management implementation (Crowley-Henry et al., 2019). Moving beyond viewing talent management as a step-by-step linear process toward aligning it with the evolving nature of careers in a changing work environment is essential (Mensah, 2019).

While some research links career theory to talent management (Yildiz & Esmer, 2021), comprehensive studies on how the job ecosystem connects to talent management practices remain scarce (Crowley-Henry et al., 2019; Gallardo-Gallardo et al., 2020). Although talent management practices directly impact individuals, the experiences and reactions of employees in the context of their careers are largely overlooked in talent management research (Gallardo-Gallardo et al., 2020; Malik & Singh, 2020).

In social security organizations, talent management is vital for improving performance and service delivery, yet it faces significant research and conceptual gaps. Despite increasing attention to talent management in public and government sectors, the unique constraints of social security organizations, such as resource limitations and specific workforce needs, have yet to be comprehensively addressed.

The first critical gap is the lack of organizational models specifically tailored to social security talent management. Existing models primarily address private and commercial sectors and cannot be easily adapted to public organizations. Developing a context-specific framework for social security is imperative.

The second gap is the underutilization of advanced technologies like ANFIS in talent management. Despite their potential to analyze complex and heterogeneous data for identifying and nurturing talent, few studies have explored their application in social security organizations.

The third gap lies in the disconnect between theoretical frameworks and practical implementation models. Most research focuses on the theoretical and conceptual aspects of talent management without adequately addressing how these theories can be applied in practice. Field studies and empirical research are needed to bridge this gap.

Lastly, further research is needed to examine the impact of talent management on job satisfaction and employee efficiency in social security organizations. Such studies can develop practical solutions to improve employee performance and positively impact service quality.

Given these gaps, the present study aims to design a talent-oriented organizational model using ANFIS to enhance the efficiency and effectiveness of social security organizations. By leveraging ANFIS's capabilities for processing heterogeneous data and adapting to dynamic conditions, this research seeks to develop a comprehensive and practical model to help social security managers and decision-makers identify and nurture key talents, improve employee motivation and satisfaction, and achieve strategic organizational objectives.

This study explores theories and concepts related to talent management and ANFIS, aiming to address the strengths and weaknesses of social security organizations and their specific needs. The ultimate goal is to create a model that effectively links organizational objectives with individual capabilities. By offering practical solutions, this research aspires to enrich organizational management literature, particularly in applying innovative analytical methods, and enhance the quality of social security services.

2- Literature Review

Talent-Oriented Organizations and Talent Management

In today's competitive world, organizations need to optimize their human capital to achieve sustainable competitive advantage. The concept of a talent-oriented organization refers to organizations that prioritize the identification, development, and management of talent in their strategic goals (Collings & Mellahi, 2009). This approach requires the use of advanced tools and models to assess competencies, predict future needs, and facilitate organizational learning (Lewis & Heckman, 2006).

Research indicates that talent-oriented organizations can achieve higher levels of productivity and innovation by attracting talented individuals and developing their capabilities (Michaels et al., 2001). In this regard, employing modern technologies such as big data analytics and artificial intelligence plays a crucial role in advancing these organizations.

Talent Management in Social Security Organizations

Social security organizations, as entities responsible for providing supportive and welfare services to societies, play a critical role in managing human capital. These organizations need to attract and manage competent and effective employees to deliver quality services to the community (ILO, 2017). Designing and validating talent management frameworks tailored to the specific needs of social security is therefore of particular importance (Gupta & Shaw, 2014).

Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are advanced tools in the field of machine learning that combine fuzzy logic and neural networks (Jang, 1993). This model leverages the learning capabilities of neural networks and the interpretability of fuzzy logic, enabling the modeling of complex problems and more accurate predictions. In recent years, ANFIS has been widely applied in studies related to human resource management and organizational performance evaluation (Chen et al., 2015).

Research has shown that ANFIS can effectively identify and analyze factors influencing talent management, predict the outcomes of development programs, and provide optimized solutions. Combining this approach with social security organizational data can lead to the development of localized models for talent management (Kumar et al., 2020).

Integration of Talent-Oriented Organizations, Social Security, and ANFIS

The use of artificial intelligence tools for talent management in public and governmental organizations, including social security, has recently garnered the attention of researchers. These tools can assist in strategic and tactical decision-making by analyzing data and predicting trends (Lee et al., 2018).

3- Research Methodology

Research Approach

The present study is applied research in terms of its objective and descriptive-survey in nature based on the method of data collection.

Research Method

The research adopts a mathematical modeling approach using the Adaptive Neuro-Fuzzy Inference System (ANFIS).

Objective

The objective of this research is explanatory and predictive.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS stands for "Adaptive Neuro-Fuzzy Inference System." Using a set of input/output data, the ANFIS fuzzy logic toolbox function constructs a fuzzy inference system whose membership function parameters are adjusted via a hybrid method of backpropagation alone or combined with the least-squares method. This allows the system to learn through data modeling, meaning that the system learns to produce outputs for given inputs based on the training data. This process involves adjusting the membership function parameters based on a selected error criterion (Shabani-Nia & Saeed-Nia, 2007).

ANFIS is a category of adaptive networks that functionally corresponds to fuzzy inference systems. Unlike artificial neural networks, ANFIS has a fixed structure comprising five layers, with each neuron in a layer performing a specific task.

Assuming that a fuzzy system has two inputs, XXX and YYY, and one output, ZZZ, the structural equations for ANFIS are as follows:

Rule 1: If xxx is A1A1A1 and yyy is B1B1B1, then f1=p1x+q1y+r1f1 = p1x + q1y + r1f1=p1x+q1y+r1

Rule 2: If xxx is A2A2A2 and yyy is B2B2B2, then f2=p2x+q2y+r2f2 = p2x + q2y + r2f2=p2x+q2y+r2

ANFIS Structure

An ANFIS typically comprises five layers, described as follows:

1. Input Layer: Represents the system inputs.
2. Fuzzification Layer: Converts crisp inputs into fuzzy sets based on membership functions.
3. Rule Layer: Maps the relationships between input fuzzy sets using predefined rules.
4. Normalization Layer: Normalizes the outputs of the rules.
5. Output Layer: Aggregates and computes the final output based on the fuzzy rules.

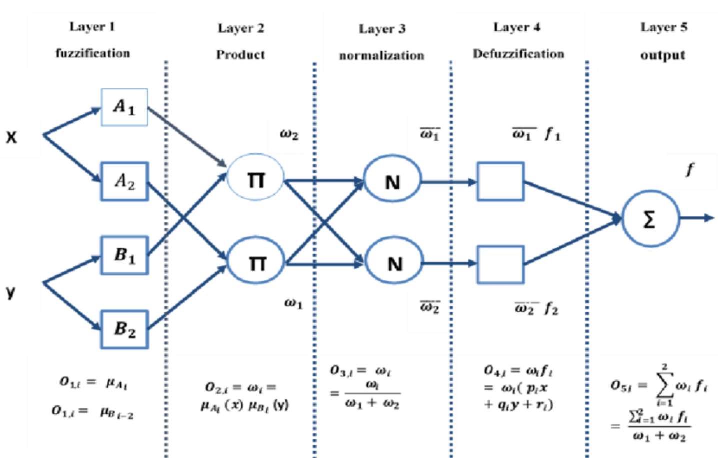

Figure 1: Five Layers of ANFIS

- Layer 1: In this layer, the inputs pass through membership functions.
- Layer 2: The output of this layer is the product of the input signals, which corresponds to the if part of the fuzzy rules.
- Layer 3: The output of this layer is the normalized output from the previous layer:

$$\overline{w}_i = \frac{w_i}{w_1 + w_2}$$

- Layer 4: The output of this layer is calculated as:

$\bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i)$

- Layer 5: The output of this layer is the final output of the system.

The mathematical model, steps, and requirements for adaptive fuzzy neural networks (ANFIS) are designed based on the conceptual model.

Implementation

To implement the mathematical model, MATLAB software is used. The model is constructed using input and output data from the conceptual model and the information obtained from the questionnaire (Shabani-Nia & Saeed-Nia, 2007).

Steps for Implementation

1. Data Collection:

Collect data related to the talent management process in the Social Security Organization, including information on identifying, attracting, developing, and retaining managers.

2. Data Preprocessing:

Prepare the data for analysis, including steps like data cleaning, coding, and transformation.

3. Modeling with ANFIS:

Develop the ANFIS model to predict the success of the talent management process in the Social Security Organization.

4. Model Evaluation:

Evaluate the model’s accuracy and performance using suitable statistical criteria.

4- Research Findings

To predict the conceptual model of the research, the following steps were taken:

1. Design a sub-FIS and a general FIS model.

2. Train these models to develop a sub-ANFIS and a general ANFIS.

3. Implement the mathematical model using MATLAB R2017a.

This study used data from 120 respondents, of which responses from 96 experts (about 80% of the total respondents) were used to train the sub-FIS and FIS models. The remaining 24 responses were used as test data to assess the sub-ANFIS and general ANFIS models.

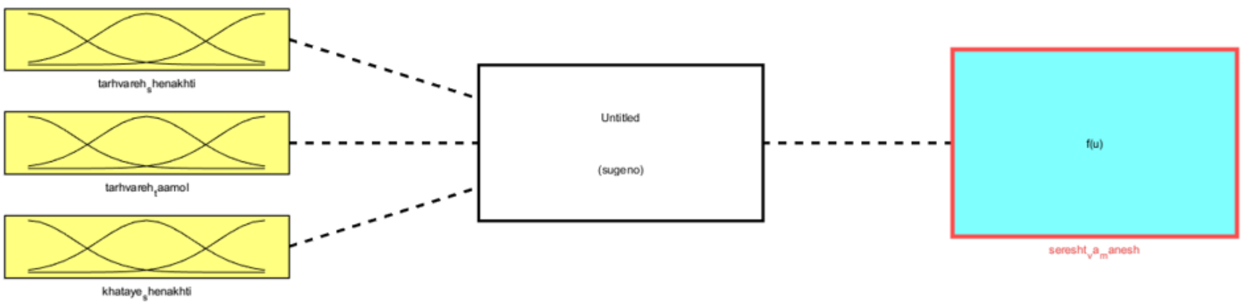

Figure 1: General Sub-FIS Diagram

As mentioned, the expert questionnaire within the organization was designed with the view that users would provide feedback regarding the inputs for each sub-model (i.e., component), as well as their general opinion on the output (i.e., overall assessment of each dimension). These data are used to train and examine these models. The structure of the sub-ANFIS model for this dimension can be seen in Figure (2).

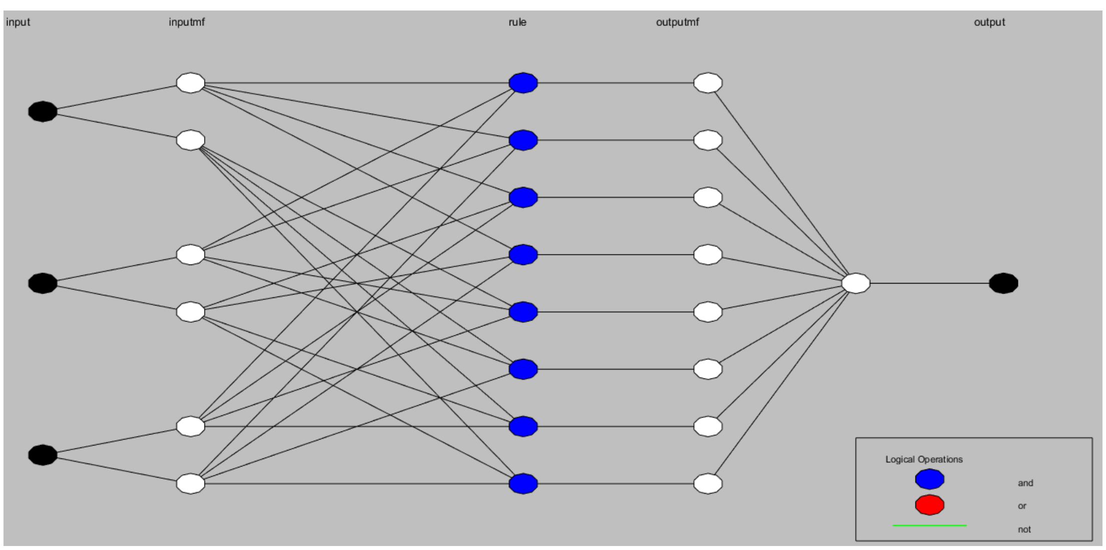

Figure 2: Sub-ANFIS Model

Using the training data, the ANFIS system was trained through a network partitioning method, and its inference rules were derived as follows:

1. If (input1 is in 1mf1) and (input2 is in 2mf1) and (input3 is in 3mf1) and (input4 is in 4mf1) and (input5 is in 5mf1), then (output is out1mf1).

2. If (input1 is in 1mf1) and (input2 is in 2mf1) and (input3 is in 3mf1) and (input4 is in 4mf1) and (input5 is in 5mf2), then (output is out1mf2).

3. If (input1 is in 1mf1) and (input2 is in 2mf1) and (input3 is in 3mf1) and (input4 is in 4mf2) and (input5 is in 5mf1), then (output is out1mf3).

4. If (input1 is in 1mf1) and (input2 is in 2mf1) and (input3 is in 3mf1) and (input4 is in 4mf2) and (input5 is in 5mf2), then (output is out1mf4).

5. If (input1 is in 1mf1) and (input2 is in 2mf1) and (input3 is in 3mf2) and (input4 is in 4mf1) and (input5 is in 5mf1), then (output is out1mf5).

6. If (input1 is in 1mf1) and (input2 is in 2mf1) and (input3 is in 3mf2) and (input4 is in 4mf1) and (input5 is in 5mf2), then (output is out1mf6).

7. If (input1 is in 1mf1) and (input2 is in 2mf1) and (input3 is in 3mf2) and (input4 is in 4mf2) and (input5 is in 5mf1), then (output is out1mf7).

8. If (input1 is in 1mf1) and (input2 is in 2mf1) and (input3 is in 3mf2) and (input4 is in 4mf2) and (input5 is in 5mf2), then (output is out1mf8).

As observed, the number of rules is 8 = 23. These 8 derived inference rules map various input values to a single output subsystem, indicating character and nature. Different combinations of component states can yield different outputs. If, in the modeling phase, instead of considering two membership functions for each component, we had considered three membership functions, the number of rules would have been 27 = 33, which would have significantly increased the complexity.

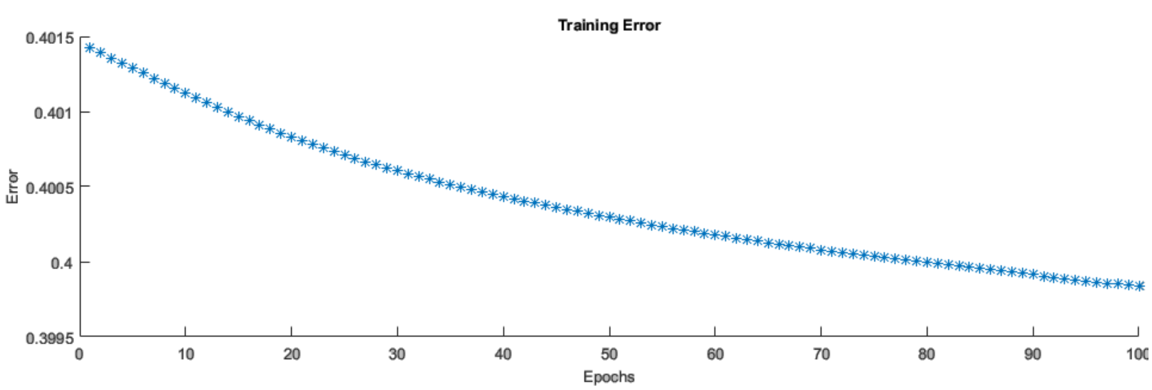

Figure 3: Displaying the Training Process to Reduce the Error Between Model Output and Training Data

Figure (3) illustrates the training process of the model. The goal is to minimize the error between the model's output and the actual output of the data. As the number of training steps increases, the error decreases. After several training cycles, the error remains constant. For this model, the error rate is 0.39 (after 2 training cycles of 100 steps each).

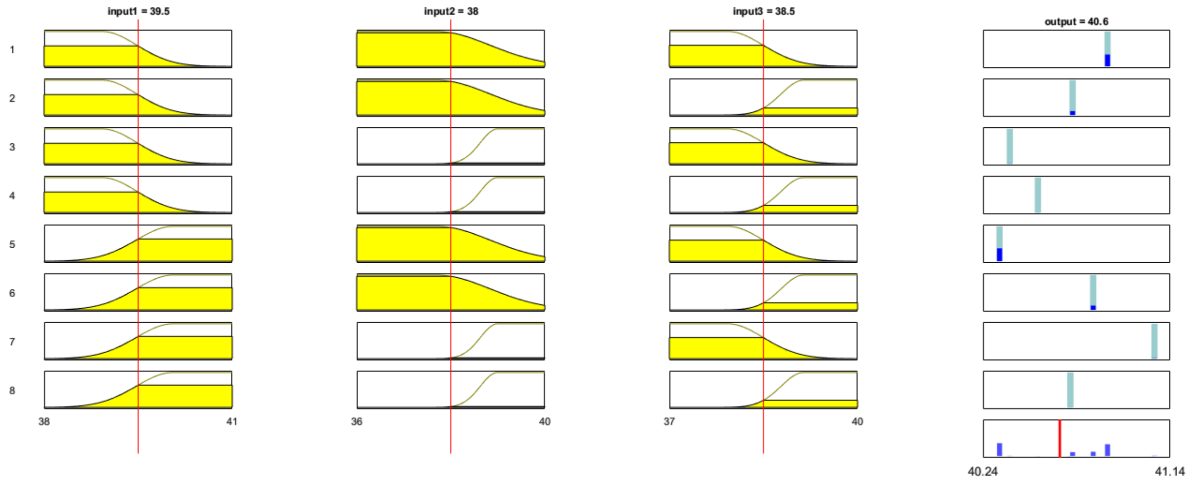

Figure 4: Displaying the Rules of the Dimension Model

In Figure (4), you can observe the impact of each input on the output, separately for each of the 8 inference rules, by changing the input values within the minimum (0) and maximum (100) ranges. Each inference rule corresponds to a row in the diagram.

Interpretation of the Fuzzy Inference Model for the First Dimension

In the following graphs, the influence of each factor on the output (First Dimension) is displayed.

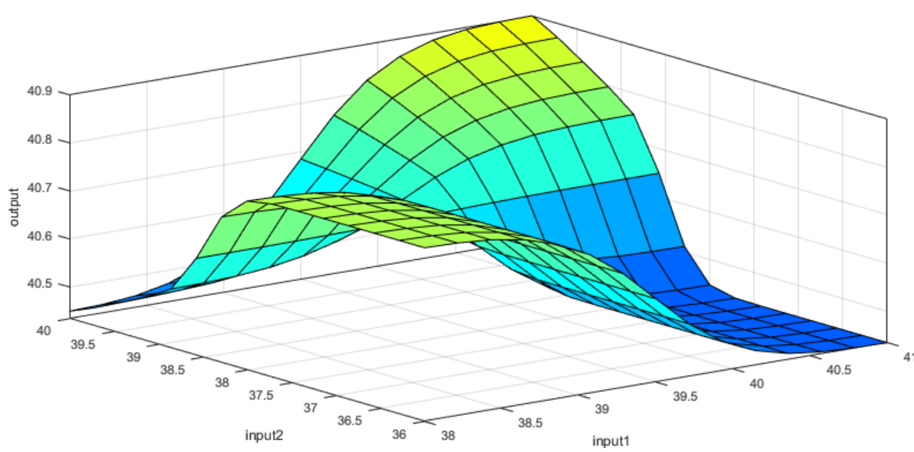

Figure 5: 3D Display of the Impact of the First and Second Components on Each Other

In Figure (5), the impact of the first and second components on the model's output is visible. In the following graphs, the individual influence of each of these components is shown separately. The combination of these two components increases the output of this model from 40.5 to 40.9.

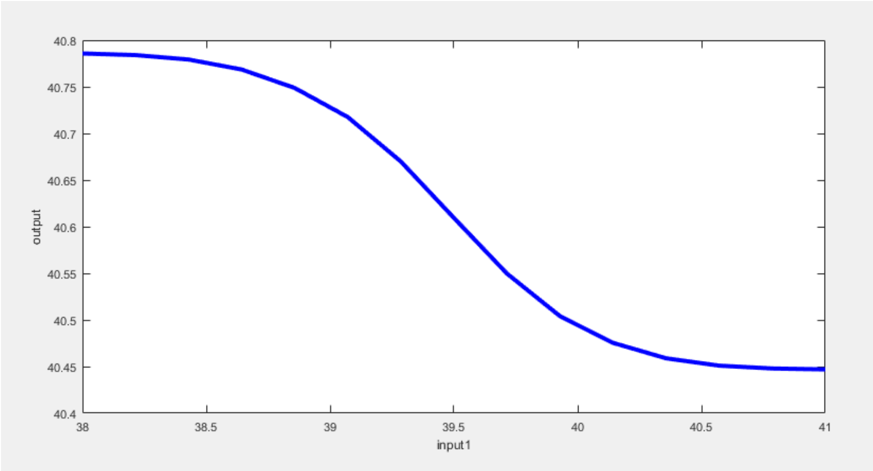

Figure 6: Display of the Impact of Changes in the Model's First Input

Similarly, Figure (6) shows that the first component has a negative impact on the output (from approximately 40.8 to 40.4). This component, with a decreasing slope, does not contribute to improving the model's output.

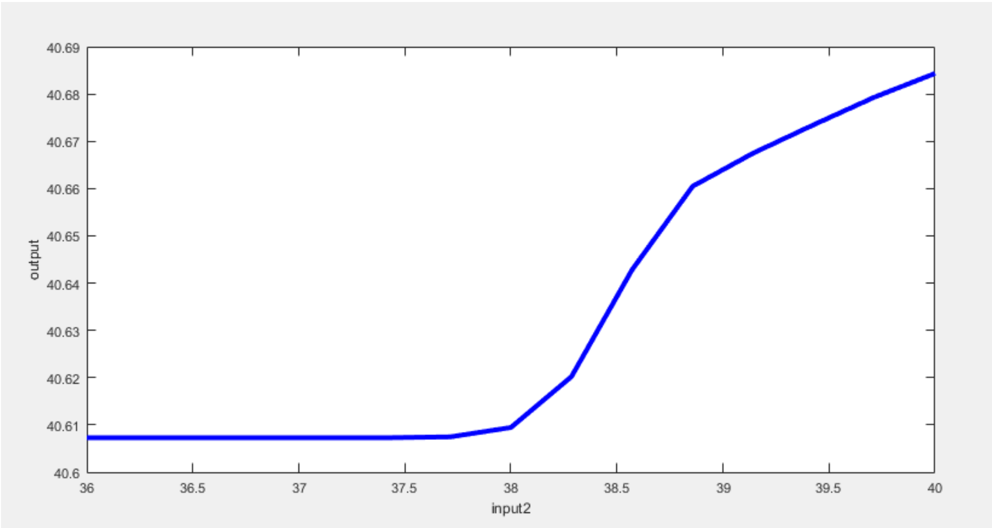

Figure 7: Display of the Impact of Changes in the Model's Second Input

Similarly, Figure (7) shows that the second component has a positive effect on the output (from approximately 40.61 to 40.69). This component, with an increasing slope, contributes to improving the model's output.

Explanation of the Fuzzy Inference Model for the Second Dimension

The graphs below show the impact of each factor on the output (second dimension).

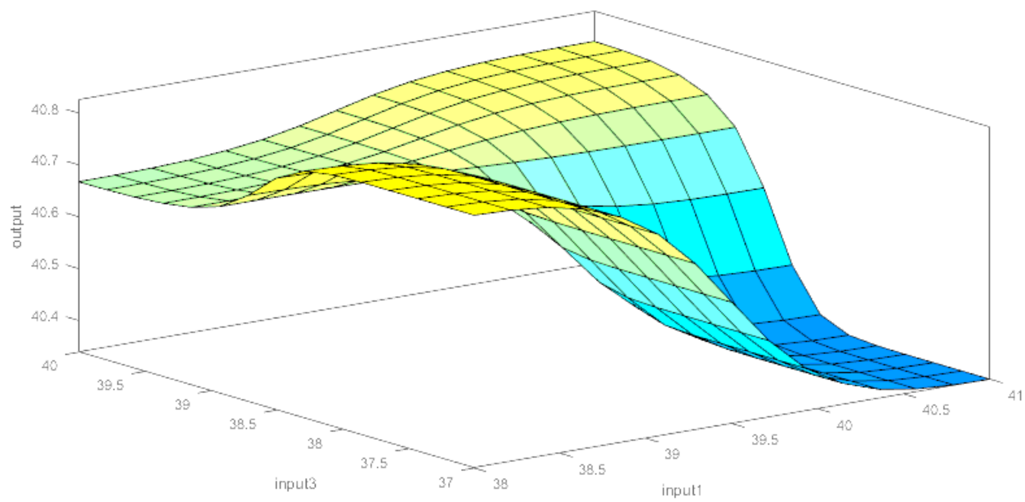

Figure 7: 3D Display of the Impact of the First and Third Components on Each Other

Figure (7) shows the impact of the first and third components on the model's output. The graphs below display the individual impact of each of these components. The combination of these two components increases the output of this model from 40.5 to 40.8.

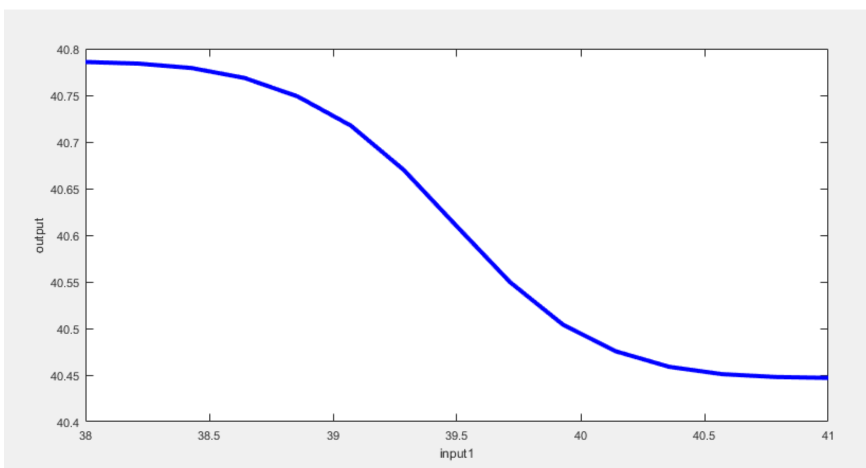

Figure 8: Display of the Impact of Changes in the First Input of the Model

Similarly, Figure (8) shows that the first component has a negative effect on the output (from approximately 40.8 to 40.4). This component does not contribute to improving the model's output, as it has a decreasing slope.

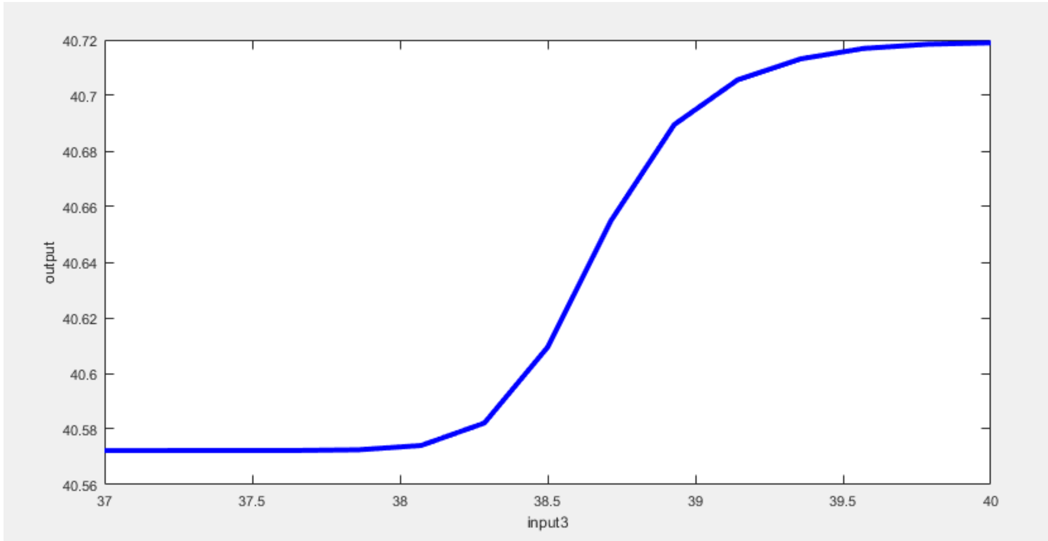

Figure 9: Display of the Impact of Changes in the Third Input of the Model

Similarly, Figure (9) shows that the third component has a positive effect on the output (from approximately 40.58 to 40.72). This component influences the improvement of the model's output with an increasing slope.

Interpretation of the Fuzzy Inference Model of the Third Dimension

In the following charts, the impact of each factor on the output (third dimension) can be observed.

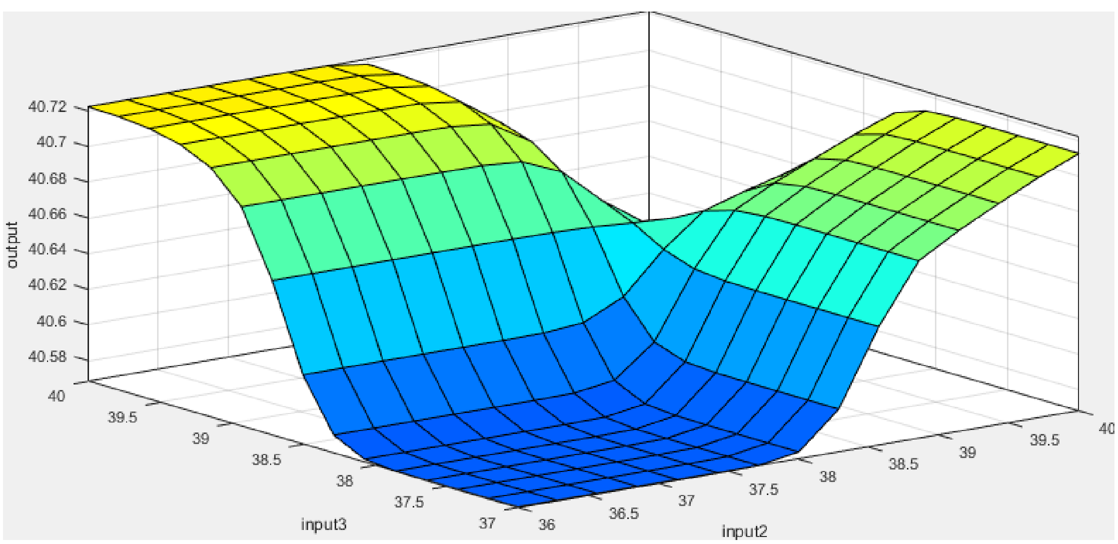

Figure 10: Three-Dimensional Display of the Impact of the Second and Third Components on Each Other

In Figure (10), the impact of the second and third components on the output of the model is visible. In the following charts, the individual effects of each of these components are observed. The combination of these two components increases the output of this model from 40.6 to 40.72.

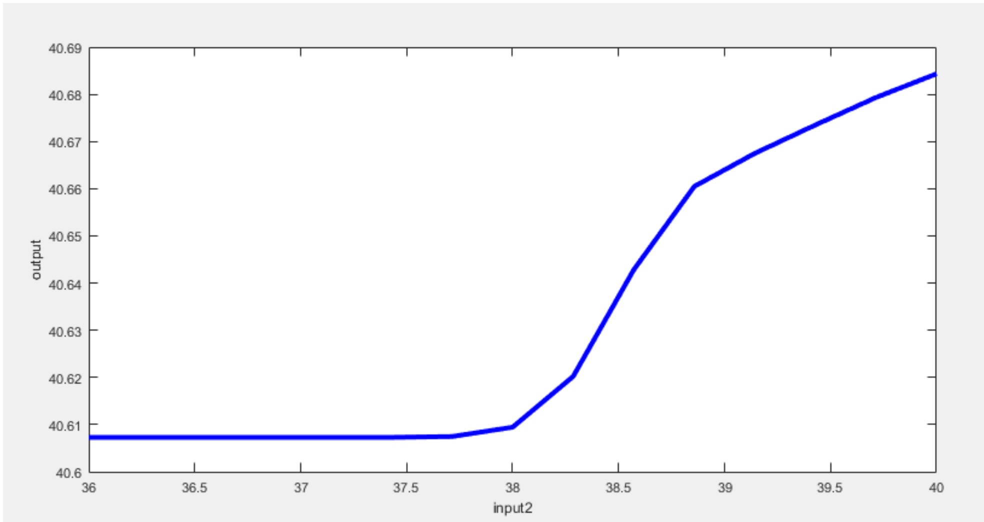

Figure 11: Display of the Impact of Changes in the Second Input of the Model

Similarly, Figure (11) shows that the second component has a positive effect on the output (from approximately 40.61 to 40.69). This component has an increasing slope, contributing to the improvement of the model's output.

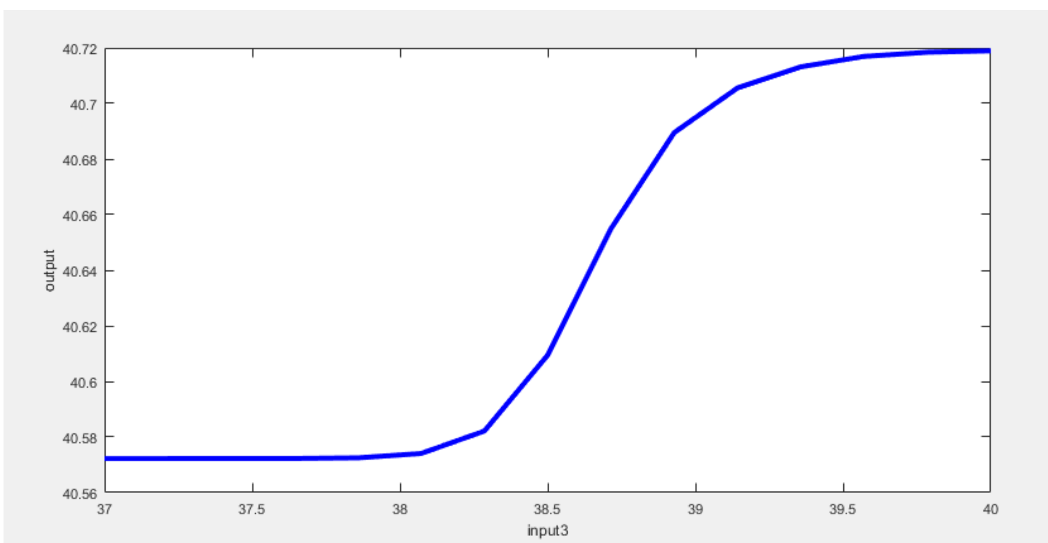

Figure 12: Display of the Impact of Changes in the Third Input of the Model

Similarly, Figure (12) shows that the third component has a positive effect on the output (from approximately 40.58 to 40.72). This component has an increasing slope, influencing the improvement of the model's output.

5- Conclusion

This research, aimed at validating the talent-oriented organizational model in the field of social security, using an Adaptive Neuro-Fuzzy Inference System (ANFIS), has yielded significant results. The ANFIS system, as an efficient tool, demonstrates the ability to adapt and learn complex patterns in organizational systems, such as social security. In this study, after defining the talent-oriented indicators and criteria within the organization, data collected from relevant samples were analyzed.

Key Findings:

1. Effectiveness of ANFIS: The use of ANFIS in validating organizational models has shown that this method can effectively analyze complex, multi-dimensional data and provide credible results.

2. Identification of Key Indicators: Talent-oriented indicators such as specialized skills, communication abilities, and innovation capabilities were identified as crucial elements for enhancing organizational productivity.

3. Direct Link to Organizational Performance: The analysis revealed that applying talent-oriented models, by improving employees' capabilities and skills, contributes to overall organizational performance.

Using talent-oriented organizational models, especially with advanced tools like ANFIS, can serve as a strategy for improving organizational performance and better alignment with environmental needs and internal and external challenges. Emphasis on recruiting, retaining, and enhancing talent has a direct positive impact on an organization's flexibility and competitiveness. Based on the findings of this research, organizations in the social security sector can tangibly improve their productivity and efficiency by implementing and developing similar models.

In conclusion, it is suggested that future research focus on enhancing these models, completing and updating the indicators, and using other artificial intelligence methods to better analyze and improve the models.

Research Limitations

- Limited Data Access: One of the limitations of this study is the restricted access to accurate data related to talent orientation in social security. Due to a lack of transparency or restricted access to some organizational data, the analysis may not fully reflect the real situation.
- Broad Definition of Talent Orientation: Talent orientation is a multi-dimensional concept with various interpretations and applications in different organizations and industries. This broadness may lead to some aspects not being properly evaluated, affecting the depth of the analysis.
- Sampling Limitations and Generalizability of Results: If the study sample is limited to specific departments or levels of the social security workforce, the

results may not be generalizable to the entire organization or other similar organizations.

- Cultural and Environmental Factors: Cultural and environmental factors that could affect talent management in different organizations were not fully considered in this study. These factors may influence the implementation and effectiveness of the talent-oriented model and could alter the results.
- Challenges in Measuring Unobservable Outcomes: Some identified outcomes, such as collaboration, organizational culture, and innovation, are qualitative and difficult to measure accurately. Limitations in measuring these factors may affect the precision and validity of the research results.
- Time and Financial Constraints: Time and financial constraints in conducting the research may have prevented a comprehensive and precise examination of some related aspects and outcomes. These limitations also impacted the choice of research methods and the accuracy of the analysis.
- Mismatch with International Research: Due to the unique cultural and structural characteristics in the country, the results of this study may differ from international research findings in the field of talent management. This could affect the generalizability of the results.

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