Saudi Airlines Cabin Crew Performance Appraisal Using Artificial Intelligence - The Adaptive Neuro-Fuzzy Inference System

Eyad W. Abdulmajeed

Faculty of Engineering, King Abdulaziz University, Jeddah, Saudi Arabia
Email Id: *eyad.w.a@hotmail.com*

Abstract: This paper targets the application of artificial intelligence in improving and developing performance through the reduction of human error and the development of fair judgment in the performance of different activities. It focuses on Adaptive Neural Fuzzy Inference System (ANFIS) for the Saudi Airlines cabin crew. Among the findings of the research was that the training error is that the difference between the training data output value and the output of the fuzzy inference system and that the fuzzy linguistic variables are not clear when applied in the performance evaluation system. The study applied a case study to analyze an adaptive neural inference system and rate it to the impact it could create on the cabin crew. The study concluded that in conducting the performance appraisal of the employees some factors such as work goals, and information on the effectiveness of goals must be considered. Also, the lack of a formal reasoning mechanism supporting the inference and evaluations is a critical challenge in performance appraisal; hence, the application of artificial intelligence in the evaluation of the performance of employees in an organization could significantly impact the employees in working towards a common goal.

Keywords: Artificial Intelligence, Performance, Human Error, Adaptive Neural Fuzzy Inference System, Fuzzy Linguistic.

I. INTRODUCTION

Employee satisfaction is very important to the success of any organization, as much as employees are satisfied productivity will be increased which will minimize the turnover rate. Therefore, companies must focus on employees' satisfaction, but maintaining employees' sanctification is a complex equation because many factors can affect the employees and make them frustrated with their jobs, and make the employees leave the organization. Thus, organizations must continuously focus on these factors to minimize the turnover rate and achieve organizational strategic goals after the initiation of the 2030 vision of Saudi Arabia, a lot of big organizations started to go with a performance appraisal system based on performance that linked with employees' promotions, and annual increments which will impact the employee's satisfaction. however, fairness and justice are the main pillars of the success of the system.

Employees with a healthy environment and great culture are motivated and productive, because they feel loyal, inspired, and recognized, so organizations must invest in developing a fair effective performance appraisal system, so good performance appraisal culture means a great relationship between employees, skills will be developed, productivity will increase, and goals will be achieved. On the other hand, employees in organizations with a poor performance appraisal system feel injustice, and frustrated. Therefore, the organization will fail.

Saudi airlines' cabin crew is the front line of the company, they have a strong effect on the reputation of the company. Keep them satisfied means better performance and of course the success of the company. Unfortunately, many complaints are received from the cabin crew department and interviewing with concerned employees, it turns out that in some cases there is bias in the evaluating process, poor judgment on the employee's evaluation, and some appraisers are evaluating the employees subjectively or emotionally. Therefore, avoiding this kind of complaint may affect the whole performance appraisal system. However, the performance appraisal system getting affected by different human factors. So, a solution must be applied before system failure.

Artificial intelligence has played a significant role, and in recent years, this phrase has grown in popularity because of advancements in the fields of artificial intelligence and machine learning. Machine learning is the branch of artificial intelligence in which computers are tasked with doing everyday tasks and are more intelligent than humans. Artificial intelligence technology has many key advantages that make it an ideal tool for almost any business environment, including automation, improvement, analysis, and accuracy. So, Artificial intelligence will be applied to design a performance appraisal system based on the machine learning tools to reduce the human error and the poor judgment on the employee’s appraisal to guarantee a fair evaluation.

To create an effective and efficient performance appraisal system, and healthy performance management environment. The process of the performance appraisal must be controlled and protected from any factors that impact the system. So, input variables for the design system have been set by conducting workshops with experts in the performance appraisals management, flight operation, and cabin crew management.

II. LITERATURE REVIEW

Machine Learning neural network (ANN)

To evaluate the quality of teaching development accurately, this proposal has been made to evaluate such case by using an advanced artificial neural network. This paper constructed evaluation system which consist of five evaluation indices. It is reliable and valid to be used in evaluating the quality of teaching development. The results proved that the model predicts effective function based on evaluation accuracy and data recognition [1].

Performance Appraisal

Performance appraisal is critical in the management of organizational systems as it assesses the performance level of employees through measuring and providing feedback on the quality of performance of employees in carrying out activities [2-5]. It is a representation of a formalized review system of evaluating team or individual performance of a specific task within an organization. Performance appraisal is critical in ensuring employees focus on goals to improve the overall organizational performance. It is used in human resource planning to assess the human resource within an organization such that the data availed is used to identify employees with the potential of promotion by developing the profiles of employees according to their strengths and weaknesses [6-7].

Performance Appraisal System

Finding the variable factors which evaluate the motivation level of employees that caused by the effect performance appraisal is the main objective of this paper. Data was collected using open ended interview and structured questionnaire, and it was analyzed by using statistical tools such as percentage, Pearson correlations and frequency distribution. The study is based on descriptive design. Performance appraisal system plays a big role in helping to improve job performance the consist assessment of performance leads to increase high employee motivation. This technique affects employees' performance and motivation in a positive way especially if it was based on an accurate job description. By having a clear performance appraisal system, bias will be reduced, and the perception of fairness will be increased. Coworkers usually know the job of their colleague better than the supervisor dose. Some managers used to be strict in rating their employees and that may affect the motivation of the employees, so the way that the manager addresses the skills gap to the employee can have a strong impact on employee's motivation. The performance appraisal should be a continuous process not just a process that happens once a year [7].

Group performance is successful in taking place in performance appraisal system of organizations. The PA systems are facing challenges and these challenges showed steady increase. It is necessary for researchers to investigate continuously about how the quality of interpersonal interaction between group members can affect group performance. Research. The results of this study are valuable for future studies which can also answer the raters' agreeableness questions. Also, the research on the actual ratees performance interaction on the relationship between agreeableness and group performance would be timely soon [8].

Fuzzy Logic

Fuzzy logic according to Bhattacharyya and Dutta [2] represents a collection of statements with conditions referred to as fuzzy rules that are based on the framework of linguistic reasoning that involves shallow knowledge. The concept arises due to human beings' manifestation in their way ways of communication such that the communication of ideas from a human is carried out through non-measurable phrases which are often moderated with the application of adverbs, adjectives to reflect the degree of significance in the idea expressed. The modification of the linguistic terms or reasoning with linguistic hedges is a basic function of natural language expression.

Neural Network

A neural network is applied in situations to develop simulations and predictions within complex systems or relationships in artificial intelligence. Neural networks are used in character recognition especially in handheld devices such that they can recognize handwritten characters. Additionally, it is used in facial recognition on matching human faces on a digital database. It can also be used in image compression such that it can process and receive a large amount of information at a time. The stock market prediction also applies neural networks to establish the market risks and the investment durations. Other areas of application include voice and speech recognition, early warning systems, controlling complex processes, and forecasting on complex systems. Also, it is used in time series analysis, machine-based translations, and medical diagnostics [9-13].

Neural Fuzzy

The third class is the hybrid fuzzy neural network systems that are similar and alike to the neural networks. The hybrid fuzzy neural network systems use learning logarithms from the neural networks theory in the determination of fuzzy sets and fuzzy rules through the input and output processing patterns [14]. Hybrid neural fuzzy systems are developed in different ways as they are focused neural networks to implement logical functions. The different fuzzy neural networks are designed to allow the comparison of different models as well as visualize the architectural differences. Some neural fuzzy difference architecture includes the fuzzy adaptive learning control network (FALCON), adaptive network-based fuzzy inference system (INFIS), generalized approximate reasoning-based intelligence control (GARIC), and neural fuzzy controller (NEFCON).

Adaptive Neuro Fuzzy Inference Systems (ANFIS)

Modeling the air emission helps improving people's health especially in traffic areas. It is an inexpensive and very efficient tool that helps developers, decision-makers, and planning engineers. Traffic management is an important tool that is used to improve air quality and enhance people's transportation. The new traffic version in this study was adopted to anticipate the air quality improvement by using the ANFIS model. ANFIS is a proven t tool that integrates the neural network and fuzzy logic. This can lead to improving the accuracy of forecasting, also, this will help decision-makers and city planners to understand the relationship between pollution and traffic [15]. This study was conducted to envisage the quality of air by using many techniques, such as ANNs and neuro-fuzzy logic.

The study of student performance has used statistical techniques. It proposed (MANFIS) in online higher education settings. The MANFIS accuracy has been tested and compared with other Multilayer neural network, general regression neural network, and radial basis function neural network. The results showed that MANFIS is an alternative prediction model for testing students' performance in the online higher settings [16-18].

II. PROBLEM STATEMENT

Employee satisfaction is very important to the success of any organization, as much as employees are satisfied productivity will be increased which will minimize the turnover rate. Therefore, companies must focus on employees' satisfaction, but maintaining employees' sanctification is a complex equation because many factors can affect the employees and make them frustrated with their jobs, and make the employees leave the organization. Thus, organizations must continuously focus on these factors to minimize the turnover rate and achieve organizational strategic goals, after the initiation of the 2030 vision of Saudi Arabia, a lot of big organizations started to go with a performance appraisal system based on performance that linked with employees' promotions, and annual increments which will impact the employee's satisfaction. however, fairness and justice are the main pillars of the success of the system.

Saudi airlines' cabin crew is the front line of the company, they have a strong effect on the reputation of the company. Keep them satisfied means better performance and of course the success of the company. Unfortunately, many complaints are received from the cabin crew department and interviewing with concerned employees, it turns out that in some cases there is bias in the evaluating process, poor judgment on the employee's evaluation, and some appraisers are evaluating the employees subjectively or emotionally. Therefore, avoiding this kind of complaint may affect the whole performance appraisal system. However, the performance appraisal system getting affected by different human factors. So, a solution must be applied before system failure.

III. OBJECTIVES

The main objectives of the study are:

- Apply a customized artificial intelligence system that will help in the performance evaluation and possible areas of development.
- Reducing the human error and the poor judgment on the employee's appraisal to guarantee a fair evaluation.

IV. METHODOLOGY

The adaptive neuro-fuzzy inference system (ANFIS)

A neuro-fuzzy system with an overall input–output behavior defined by a set of changeable parameters is known as an adaptive neuro-fuzzy inference system (ANFIS). An adaptive network is made up of nodes linked by directed links, each of which executes a function on its incoming signals to produce a single node output, and each link defines the signal flow direction from one node to the next [8-10]. Each node function is usually a parameterized function with adjustable parameters; altering these parameters changes the node functions as well as the adaptive network's overall behavior. An adaptive network's nodes execute a static mapping from their inputs to outputs. To make the construction of learning algorithms easier, all node functions are assumed to be differentiable. An adaptive network's parameters are spread across its nodes, each of which has its own set of parameters. The overall parameter set of the network is formed by combining these local parameter sets. The adaptive networks developed in this paper are equal to fuzzy systems in terms of functionality. If-Then fuzzy rules are encoded using the suggested network structure, with the result being a function of the input variables. Without using a formal model to learn from data samples, the network structure guesses a function. Fuzzy sets are thought to be useful in the logical area and for readily managing higher-order processing. The increased flexibility of neural nets created by learning is another trait that makes them more appropriate for data-driven processing.

ANFIS Architecture

Two distinct components may be identified in the network structure, namely the premise and consequence components. The architecture is comprised of five levels. The first layer receives the input values and determines their associated membership functions. It is frequently referred to as the fuzzification layer. Each function's membership degrees are computed using the premise parameter set, namely {a,b,c}. The second layer is in charge of producing the rules' firing strengths. The second layer is referred to as the "rule layer" due to its function. The third layer is responsible for normalizing the computed firing strengths, which is accomplished by dividing each value by the overall firing strength. The fourth layer accepts the normalized values and the resulting parameter set {p,q,r} as input. This layer returns the defuzzified values, which are then given to the final layer to generate the final output [19].

Develope Adaptive neuro fuzzy inference system (ANFIS).

The existing performance system is based on full cycle during the year, starts from January and ends in December. The cycle going through five phases objectives settings, feedback and couching, mid-year review, end-year evaluation, finally the calibration phases. Moreover, the appraisal overall rating is based on three pillars' objectives, competencies, and development objectives. Each pillar has specific weight. And based on these pillars the overall rating of the performance will be calculated. Finally, the final rating for the employees will affects the rewards program for the employee, such as annual increment, bonus, promotion.

1) *Optimization Method*

The Fuzzy Logic Toolbox program utilizes back-propagation alone or in conjunction with a least-squares method to train a fuzzy system using ANFIS. This training procedure adjusts the settings of a FIS's membership function so that the system accurately represents your input/output data.

The approach used in ANFIS and Neuro-Fuzzy Designer to update membership function parameters is a hybrid one that combines backpropagation for parameters associated with input membership functions and least squares estimation for parameters connected with output membership functions.

The ANFIS model can produce crisp numerical values and includes the following steps:

(1) defining input and output variables by linguistic statements.

(2) deciding on the fuzzy partition of the input and output spaces.

(3) choosing the membership functions (MFs) for the input and output linguistic variables.

(4) deciding on the types of fuzzy control rules.

(5) designing the inference mechanism.

(6) choosing a de-fuzzification procedure.

Fuzzy clustering approach is used to generate objective number of rules which are based on the clustering of input and output data sets, the level of fuzziness of clusters, and the membership functions. In this approach, the number of rules is usually equal to the number of output clusters regardless of the number of input variables. It considers each data point as a possible cluster center and determines a probability of the cluster center being defined depending on the density of nearby data points. To generate an ANFIS structure, a cluster radius must be specified to indicate the range of influence of the cluster. The illustration in Figure 1 shows a particular situation in which the data space is taken to be a unit hypercube. By specifying a modest cluster radius, the data is divided into several little clusters, resulting in many rules. Consider an M-dimensional space containing a collection of n data items x1,...,xn. Given that each data point represents a potential cluster center, Eq (1) determines the frequency value for data point xi.

$$D_i = \sum_{j=1}^{n} \exp\left(-\frac{\|x_i - x_j\|^2}{(r_a/2)^2}\right) \quad (1)$$

where r is a constant that is positive. The data points located close to the initial cluster center xc1 will have considerably lower density values. After adjusting the density measure for each c data point, the next cluster center xc2 is chosen and all data point density measures are updated once again. This procedure is continued until an appropriate number of cluster centers has been created. These cluster centers will serve as the premise centers for a zero-order Sugeno fuzzy model [8-10, 16-17]. For example, if the ith cluster's center is ci in an M-dimensional space, ci may be decomposed into two component vectors pi and qi, where pi is the input component containing the first N element of ci and qi is the output component including the final M-N elements of ci. Then, for a given input vector x, Eq. (2) defines the degree to which fuzzy rule I is satisfied. Five cluster centers were identified in this research for the 2612 data set. The number of fuzzy rule sets would be equal to the number of cluster centers, each of which would represent a cluster feature as shown in Fig. 1.

$$\mu_i = \exp\left(-\frac{\|x - p_i\|^2}{(r_a/2)^2}\right) \quad (2)$$

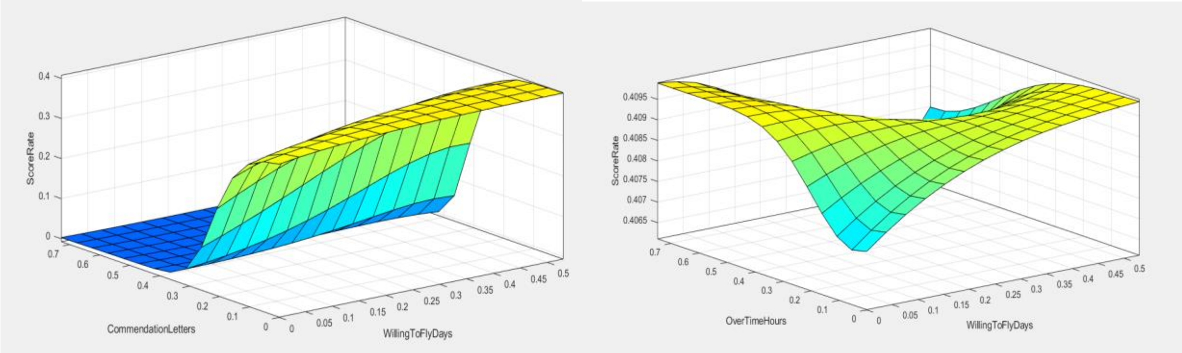

Fig. 1: Control action surface after training.

2) Fuzzy reasoning, fuzzy rules and membership functions

Fuzzy rules and fuzzy reasoning provide the foundation of fuzzy inference systems, the most widely used modeling technique based on fuzzy sets [8-10]. Fuzzy reasoning is an inference technique that uses a collection of fuzzy If-Then rules and known facts to generate conclusions. The reasoning process for a first order Sugeno fuzzy model is shown in Fig. 2. Because each rule produces a distinct result, the aggregate output is calculated using a weighted average, eliminating the time-consuming procedure.

The ANFIS's input parameters are as follows: Willing To Fly Days (WTFD), Commendation Letters (CL), Good Evals (GE), OverTime Hours (OTH), Weight Status (WS), Absence (Ab), Sick Leave (SL), Scattered SickLeave (SSL), Warning Letters (WL), Disc. Actions (DA), and Bad Evals (BE)' and the output is the 'Employee's Performance Appraisal (EPA)'. Fuzzy linguistic variables are unclear attributes that are often applied in performance evaluation systems. These linguistic variables are unclear, ambiguous, and insufficient. fuzzy terms. They are introduced and expressed by fuzzy linguistic values such as 'Unsatisfactory (A1), Need improvement (A2), Meet expectations (A3), Exceed expectations (A4), Outstanding (A5), as is given in Fig. (3).

µA(x), where x represents an employee's performance in set A. Fuzzy rules are mathematical connections that translate inputs to outputs and are composed of fuzzy linguistic variables and their associated term sets. The terms "fuzzy If-Then rules" or "fuzzy conditional statements" refer to fuzzy If-Then rules. They are often employed in daily linguistic expressions. ANFIS models are constructed using fuzzy rules. For example, If (WillingToFlyDays is A5) and (CommendationLetters is A5) and (GoodEvals is A5) and (OverTimeHours is A5) and (Weight_Status is A5) and (Absence is A5) and (Sick_Leave is A5) and (ScatteredSickLeave is A5) and (WarningLetters is A5) and (Disc._Actions is A5) and (BadEvals is A5) then (ScoreRate is outstanding) is a complete rule defining the relations of input and output linguistic variables.

$$\mu_i = \exp\left(-\frac{\|x - p_i\|^2}{(r_a/2)^2}\right) \qquad (3)$$

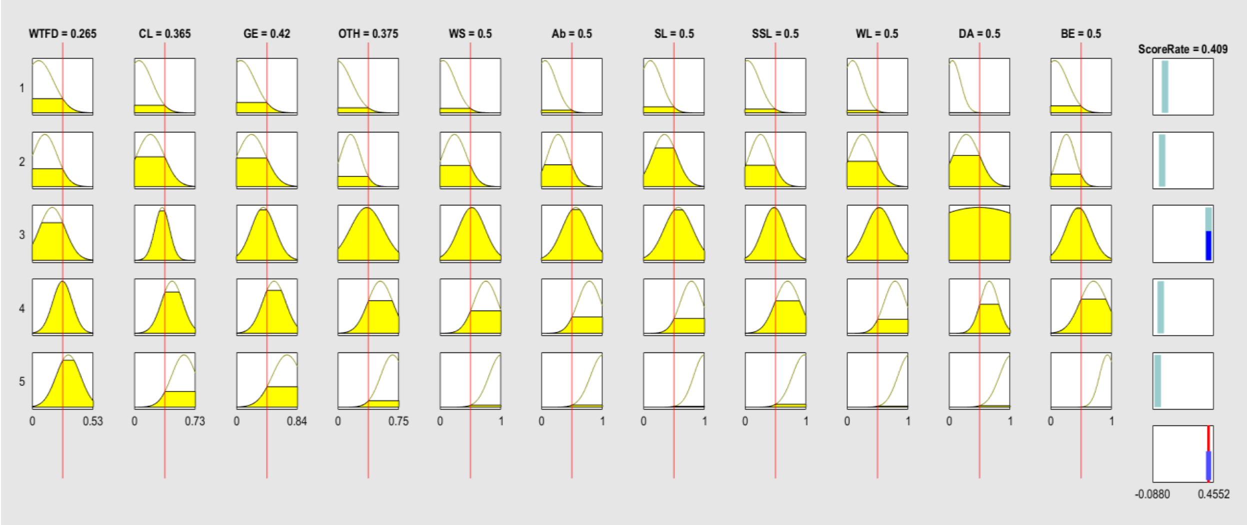

Fig. 2. Fuzzy reasoning procedure for Sugeno model of the performance score rate.

a) b)

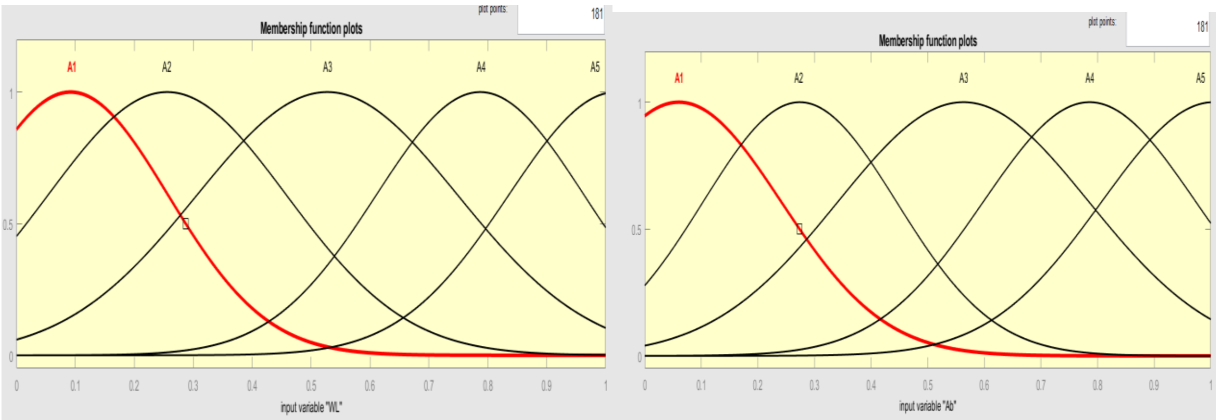

Fig. 3. Fine-tuned membership functions of 'WarningLetters (a), Absence(b)' as input variables.

The rule set in Eq. (3) shows the reasoning process and the corresponding equivalent ANFIS architecture with comparable functions for nodes in the same layer. According to Mendel (2001), fuzzy If-Then rules are production rules that have antecedent and consequence components. In a Sugeno fuzzy model, a typical fuzzy rule has the form of Eq. (3), where A1..., A5 are fuzzy linguistic values describing the linguistic variables. The terms 'WTFD is A1' and 'Ab is A2' are antecedents. In the consequence, z=fi(x,y) is a crisp function, and the values returned by this function are also crisp values. Typically, z=fi(x,y) is a polynomial in the input–output variables x and y, but it may be any function as long as it estimates the model's output inside the fuzzy area defined by the rule's antecedent. When z=fi(x,y) is a first order polynomial, the resultant ANFIS is referred to as a Sugeno fuzzy model of the first order. Furthermore, given certain modest constraints, a zero-order Sugeno fuzzy model is functionally identical to a Radial Bases Function Network. Sugeno's fuzzy model, often referred to as the model, is used to create a systematic method for generating fuzzy rules from a given input–output data set [20-21].

Architecture of hybrid learning and adaptive neuro-fuzzy inference system

The neural network structure is shown in Fig. 4. A gradient vector facilitates the calculation of MFs parameters (or their modification) since it offers a measure of how effectively the ANFIS is modeled using the input/output data for a particular set of parameters. After constructing the MFs, one of many optimization algorithms may be used to modify the parameters to decrease the measurement error defined by the sum of the squared which is the difference between actual and desired outputs. however, During the learning process, the parameters linked with the MFs will change.

The output of the i^{th} node is denoted in layer l as Ol,i which is given in Eq. (4).

Layer 1: every node i in this layer is an adaptive node with a node function

$$O_{1,i} = \mu_{A_i}(\mathrm{WL}), \quad for\ i = 1, 2, or \qquad (4)$$
$$O_{1,i} = \mu_{A_{i-2}}(\mathrm{Ab}), \quad for\ i = 3, 4,$$

Where, WTFD, CL, GE, OTH, WL, Ab are the input to node i and A1,...,i is the linguistic label such as ‘outstanding’, ‘meet expectations’ or etc. associated with this node. In other words, Ol,i is the membership grade of fuzzy set A1,...,i (linguistic labels) and specifies the degree to which the given assessment tool WTFD (or Ab) satisfies the quantifier A1,...,i. The membership grade of each linguistic value A1,...,i can be parameterized and calculated using Eq. (5).

$$\mu_A(x) = bell(x; a, b, c) = 1 \Big/ \left(1 + \left|\frac{x - c_i}{a_i}\right|^{2b}\right) \qquad (5)$$

where ai, bi, and ci are the parameter values. The parameters ci and ai may be modified to change the MF's center and width, while bi is used to modify the slopes at the MF's crossover points with the following MF. where the values of these parameters changing, the bell-shaped function contains a variety of MFs for the fuzzy linguistic set A1,...,i. This layer's parameters are referred to as premise parameters [8-10].

Layer 2: Each node in this layer is a fixed node, with an output of all incoming signals provided in Eq. (6).

$$O_{2,i} = w_i = \mu_{A_i}(Q)\mu_{A-2}(M)\ldots\mu_{A-n}(F), \quad i = 1, 2\ldots, n \qquad (6)$$

Fig. 4. ANFIS architecture for a eleven input single-output Sugeno fuzzy model. Each node output represents the firing strength of a rule. In general, any other T-norm operators that performs fuzzy AND can be used as to node function in this layer.

Layer 3: Every node in this layer is fixed. The ith node calculates the ratio of the ith rule’s firing strength to the sum of all rules’ firing strengths using Eq. (7).

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2. \qquad (7)$$

Outputs of this layer are called normalized firing strengths.

Layer 4: Every node i is an adaptive node with a node function O4,i as in Eq. (8).

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i Q + q_i M + \cdots + m_i F + r_i) \qquad (8)$$

where wi is a normalized firing strength from Layer 3 and {pi, qi,...,mi, ri}are the parameter sets. Parameters in this layer are referred to as consequent parameters.

Layer 5: the single node in this layer is a fixed node labeled R, which computes the overall output as the summation of all incoming signals as calculated by Eq. (9)

$$\text{Overall output } z = O_{5,1} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{9}$$

Model Training and Testing Data Set

Developing an ANFIS model to evaluate the cabin crew performance, 2612 data instances are used for the development of the ANFIS model. The data is divided into two data sets training data and testing data.

To train a fuzzy system using neuro-adaptive methods, input/output training data must be collected via experiments or simulations of the system being modeled. By and large, ANFIS training works well when the training data is completely representative of the features of the data being modeled by the trained FIS. The training data has been specified In the MATLAB workspace, by creating an array, each row contains a single data point with the final column containing the output which is the score rate value, and the remainder containing the input values. Then the data will pass to the ANFIS function's training data input by loading into the Neuro-Fuzzy Designer app.

The testing data set allows evaluating the results of the fuzzy inference system's generalization capability. The data checking set has been used for model validation; model validation means that the model will begin to overfit the training data set at some point during training. In general, as training proceeds, the error in the checking data will be decreasing until the overfitting happened. in some point the error for the checking data will increase. To account for overfitting, the FIS trained on the training data is compared to the testing data, and the membership function parameters are chosen in such a way that the checking error is minimized if the checking error indicates model overfitting. However, we must load the eleven parameters' inputs along with the output parameter in MATLAB to check the results for both the Test and Train the data. Where it identified when to start training ANFIS.

V. RESULTS AND DISCUSSION

In this paper, we focused on development of a data driven ANFIS model using a real dataset obtained from cabin crew performance over a year. The studied ANFIS is a soft computing approach and a general feed-forward multilayer neural network for fuzzy modeling and decision systems. A difficulty facing various existing neuro-fuzzy hybrid learning methods is that the learning is supervised and thus requires training information on the subject domain. In this approach, the fuzzy logic components are directly integrated in the neural networks. The input and output nodes represent the input states and control signals, respectively, and in the hidden layers there are nodes that code membership functions and rules. The learning algorithm used to build rule nodes and training the membership functions is based on hybrid algorithm.

Five cluster centers were identified in this research for the 2612 data set. The number of fuzzy rule sets would be equal to the number of cluster centers, each of which would represent a cluster feature (refer figure 1).

The reasoning process for a first order Sugeno fuzzy model is shown in Fig. 2. Because each rule produces a distinct result, the aggregate output is calculated using a weighted average, eliminating the time-consuming procedure.

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In this study, the ANFIS contains a total of 170 fitting parameters, of which 110 are premise (nonlinear) parameters and 60 are consequent (linear) parameters. The size of input–output data set is large enough to lay down the ANFIS model and to fine tune the membership functions. A total of 2220 training data and 700 testing data have been uniformly sampled from the input ranges and used. The training error is the difference between the training data input value, and the output of the fuzzy inference system. However, we must load the eleven parameters' inputs along with the output parameter in MATLAB to check the results for both the Test and Train the data. Where it identified when to start training ANFIS, however, after running the ANFIS model in the MATLAB with 3000 epochs shows that Number of nodes: 134, Number of linear parameters: 60, Number of nonlinear parameters: 110, Total number of parameters: 170, Number of training data pairs: 2220, Number of fuzzy rules: 5, And the Minimal training RMSE is 0.00290903.

VI. CONCLUSION AND RECOMMENDATION

In conclusion, several reasons exist to assess the performance of the employees. Performance assessment gives feedback on the effectiveness of the quality of the work goals and the development of employees, the extent to which the goals have been achieved, and information on the effectiveness of goals. Different evaluation methods have been used to evaluate the employees in diffracts areas. A variety of them also exist in different countries around the world. In mostly used statistical methods, different scores of each assessment tool are added up based on determined weights to obtain a single score for an individual employees' performance. However, evaluators usually lack a formal reasoning mechanism to support the inference and typically evaluations are decided according to given marking schemes, experiences, sensitivities, and standards. Thus, marks assigned by an evaluator are only approximations. Conversely, the company performance evaluation involves the measurement of ability, competence and skills which are fuzzy concepts and can be approximated by fuzzy linguistic terms. Eventually, linguistic terms can be awarded to a single employee's achievement as well as a group of employees who had already have working on the same goal. Finally, I recommend applying artificial intelligence to evaluate human behavior, skills, and knowledge progress and development in different areas.

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REFERENCES

[1] Al Bassam, N. & Zayegh, A., 2018. Neural Network Principles and Applications. In: Digital Systems. s.l.:IntechOpen, pp. 1-16.

[2] Bhattacharyya, S. & Dutta, P., 2012. Fuzzy Logic: Concepts, System Design, and Applications to Industrial Informatics. In: A. Q. A. Mohammad Ayoub Khan, ed. Handbook of Research on Industrial Informatics and Manufacturing Intelligence: Innovations and Solutions. Hershey, USA: IGI Global, pp. 33-71

[3] Chen, G. & Pham, T. T., 2001. Introduction to Fuzzy Sets, Fuzzy Logic, and Fuzzy Control Systems. Boca Raton, Florida: CRC Press LLC.

[4] Dernoncourt, F., 2013. Introduction to Fuzzy Logic, Massachusetts: Massachusetts Institute of Technology.

[5] Dijk, D. v. & Michal, S. M., 2015. Performance Appraisal and Evaluation. In: J. D, ed. International Encyclopedia of the Social & Behavioral Sciences. Negrev: Oxford: Elsevier, pp. 716-721.

[6] Gurney, K., 1997. An introduction to neural networks. London: UCL Press Limited.

[7] Idowu, A., 2017. Effectiveness of Performance Appraisal System and its Effect on Employee Motivation. Nile Journal of Business and Economics, 3(5), pp. 15-39.

[8] Jang, J. S. R., & Sun, C. T. (1993). Functional equivalence between radial basis function networks and fuzzy inference systems. IEEE Transactions on Neural Networks, 4, 156–159.

[9] Jang, J., & Sun, C. (1995). Neuro-fuzzy modeling and control. Proceedings of IEEE, 83, 378–406.

[10] Jang, J. S. R., Sun, C. T., & Mizutani, E. (1997). Neuro-fuzzy and soft computing. New Jersey: Prentice-Hall.

[11] Klement, E. P. & Slany, W., 1997. Fuzzy Logic in Artificial Intelligence. In: J. G. W. A. Kent, ed. Encyclopedia of Computer Science and Technology. s.l.:Marcel Dekker, pp. 179-190.

[12] Kruse, R., 2008. Fuzzy Neural Network. Scholarpedia, 3(11).

[13] Mijwil, M. M., Esen, A. & Alsaadi, A., 2019. Overview of Neural Networks, Baghdad: Baghdad College of Economics Sciences University.

[14] Mitra, S., & Hayashi, Y. (2000). Neuro-fuzzy rule generation: Survey in soft computing framework. IEEE Transactions on Neural Networks, 11(3), 748–768.

[15] Figueiredo, M., & Gomide, F. (1999). Design of fuzzy systems using neuro-fuzzy networks. IEEE Transactions on Neural Networks, 10(4), 815–827.

[16] Taylan, O. (2006). Neural and fuzzy model performance evaluation of a dynamic production system. International Journal of Production Research, 44(6), 1093–1105.

[17] Cordon, O., Gomide, F., Herrera, F., Hofmann, F., & Magdalena, L. (2004). Ten years of genetic fuzzy systems: Current framework and new trends. Fuzzy Sets and Systems, 141, 5–31.

[18] Zadeh, L. A. (1972). A fuzzy set theoretic interpretation of the linguistic hedges. Journal of Cybernetics, 2, 4–34.

[19] Mendel, J. M. (2001). Uncertain rule-based fuzzy logic systems: Introduction and new directions. New Jersey: Prentice-Hall PTR.

[20] Berenji, H. R., & Khedkar, P. (1992). Learning and tuning fuzzy logic controllers through reinforcements. IEEE Transactions on Neural Networks, 3, 724–740.

[21] Takagi, T., & Sugeno, M. (1985). Fuzzy identification of systems and its application to modeling and control. IEEE Transactions on Systems Man and Cybernetics, SMC15, 116–132.

