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A Model for Analyzing Employees Career Path Based on Neuro-Fuzzy Network and Simulated Annealing Algorithm

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Abstract

In today's business world, the competitiveness and survival of any organization depends on the availability of human resources appropriate to the jobs of that organization, so having an intelligent career path model helps organizations to analyze career path of employees scientifically and efficiently in the best possible time and meet their manpower needs more quickly**.** In this paper, we present a model for analyzing the career path of employees using neuro-fuzzy network and simulated annealing meta-heuristic algorithm. in the experimental study the outputs of model show potential of each employee to be placed in different jobs of organization, to analyze the career path of employees with the model obtained 10-year data of the employees of a transportation company in Tehran was used. Finally, by using defuzzification a percentage is determined for each of the outputs which predicts the potential of each employee to be placed in organizational jobs and helps the organization to appointment of employees in different jobs. For optimization the simulated annealing algorithm has been compared with the genetic algorithm and ant colony optimization algorithm, that the simulated annealing algorithm shows better results**.** the presented model has very good prediction accuracy.

Keywords: Career path**,** Neuro-fuzzy network, Simulated annealing algorithm.

Introduction

Today, human resources have become a very important resource for the development of companies and businesses. Knowledge, skills and the competencies related to the human resources are being converted into an important factor for an organization in establishing competitive advantage, therefore, the management of human resources becomes more important for its goal is directing the entire energy of employees towards achieving the strategic goals of a Company (Lukovac et al., 2017). Hatch (2013) has stated that the implementation of the strategy of any organization requires three factors, one of those creating the structures and the policies of human resources. The role of human resources in organizations is very important because they are rare, valuable and non-copyable. Although the presence of talented and capable employees is not the only competitive advantage of any organization, but it can compensate for the lack of other resources in some cases. Human resources have unlimited capability, that guarantees sustained remaining in the competitive market. Hence, attention to developing human resources in the organization is an inevitable necessity. There are many methods to develop human resources, that developing the career path is one of its main and important methods. Career path and promotion are effective in the employee performance and lead to employee satisfaction or dissatisfaction. Alignment and efficiency in response to market demands and simultaneously adapting to environmental changes through innovation and discovery of new solutions can help improve the performance of the organizations (Vahedi et al., 2024). The increasing competition in businesses, emergence of new technologies, establishing large companies in several branches inside a country or in the international level make difficult direction of career path in traditional way. Therefore, creating an intelligent model for determining the career path of employees based on the existing data becomes very important an intelligent model of career path based on the human resources data could be highly efficient in today uncertainty business environment, it also can be associated with the changes appeared in the Organization and increase the productivity of the human resource. Using the neuro-fuzzy networks as a new method could direct us to a professional and advanced model of career path. This model can be adapted and implemented based on employee data in any organization.

The results of Sharafizadeh et al. (2021) showed that there is a significant relationship between the main factors and their sub-factors in the conceptual-analytical model of the research and also the results showed that the fit of the general research model is appropriate and strong. In general, it can be said that between the first step of the career path with the second step of the career path, between the second step of the career path with the third step of the career path and between the third step of the career path with the fourth step of the career path of employees There is a direct and significant relationship between start-up business employees in the conceptual-analytical model of career path.

Although the career path questionnaire was prepared by Shine in 2006(Kermani et al.,2023) the methods based on the questionnaire are not enough to meet the needs of employees' career path in today's business world. In the following, we explain researches that have been conducted in the field of career paths using intelligent models or fuzzy methods.

In research of Lukovac et al. (2017) The Boston Consulting Group (BCG) matrix used for developing the portfolio of human resources based on neuro-fuzzy and the Simulated Annealing algorithm (SA) used for simulation. This model enables decision makers to assess and evaluate the potentials of human resources in connection with the environment and the environmental conditions. The goal of making this model is creating a design to improve and promote the potential of the employees in an organization. This model considers the input variables by using the fuzzy complexes which are shown by Gauss functions. By analyzing the literature related to the portfolio models of human resources one could observe that using the fuzzy logic, the neuro-fuzzy models, linear and dynamic planning, the explorative and meta-heuristic models are rarely used. In the papers that discuss the subject of modelling human resources and have analyzed the portfolio by only using the CRISP techniques, it is proved to be inflexible and unable to utilize the uncertainty which exists in the modelling process. Using the fuzzy method can appear a suitable method to remove this issue (Lukovac et al., 2017).

One of the areas in which neural networks can create a real quantum leap is human resources, analyzing a large volume of data and presenting smart models are among the works that can be carried out on the human resources data by using the neural network. Lukovac et al. (2017) in their paper used a neuro-fuzzy network to present a model for the portfolio of human resources; and, this model led us to take idea and by using a similar method, extract the career path model of employees by using the neuro-fuzzy network. In research of Lukovac et al. (2017) to optimize neuro-fuzzy network, the Simulated Annealing algorithm (SA), the Back Propagation algorithm (BP) as well as hybrid algorithm were used; and as the Simulated Annealing algorithm yielded better results and less errors; Therefore, in our research, we have used Simulated Annealing algorithms (SA) to optimize the neuro-fuzzy network and compare result with Genetic and Ant Colony Optimization algorithms. Currently, career planning has become more important than independent career decisions

There is relatively little information about the factors affecting career goals and when and how to determine career goals. From the point of view of boundaryless careers, employees, rather than organizations, are responsible for drawing their own maps, however, career paths are possible paths for individuals. However, groups can be an alternative to institutionalized job structures and a compass to help define and create career goals within the career management process (Greco & Kraimer, 2020).

A relatively modern contribution from management science is the person-job theory, which suggests increasing job satisfaction for individuals. When the individual characteristics match the job conditions, better productivity will arise for the employer. The dynamics of multidimensional understanding of career guidance, the complexity and sensitivity of the data involved means that this approach may be better implemented using computers. Systems that can receive and logically analyze large amounts of information from multiple sources are well suited to produce coherent, sustainable, and actionable career path decisions (Hassan et al., 2022). Sembiring et al. (2022) show in response to the question: Does career development and work motivation affect employee performance through job satisfaction as an intervening variable? research was conducted on 85 employees; primary data was obtained in the form of a questionnaire and secondary data was obtained through documentary studies. In this research, in the technique of data analysis, quantitative data has been used, which has been processed with SPSS software version 25.

The dual process theory of career decision-making is a result of the combined and critical reflection of career decision-making and related models in the field of contemporary social psychology of career development. DTC presents ongoing decision uncertainty as a salient condition in contemporary career decision-making, and its theoretical framework and predictive model provide the conceptual and empirical basis of DTC, respectively (Xu & Flores,2023). Career development practices should support the development of individuals and the needs of the organization. Career development plays an essential role in ensuring effective quality management (Els & Meyer,2023). Kolhe (2023) presented an online career prediction system using supervised machine learning based on user profiles that tries to create a model for the user and predict the career path in an accurate way.

Machine learning (ML) approaches provide a potential way forward as they can effectively take into account complexities in the relation between interests and career choices (song et al.,2024). As artificial intelligence (AI) use expands within organizations, its influence is increasingly permeating careers and vocational domains. However, there is a notable lack of structured insights regarding AI's role in shaping individual career paths across career stages (Bankins et al.,2024). siswipraptini et al. (2024) presents a personalized career-path recommendation model (CPRM) to provide guidance and help college students choose information technology jobs. The design of the CPRM is based on the personalized Naïve Bayes (p-NB) algorithm with three primary sources: job profiles, personality types, and subjects.

Career selection is one of the most important decisions every person faces in their life. Finding the right career path can be a complicated task, particularly in choosing careers with similarly required proficiencies. One of the critical factors affecting a person's career success is their personality, and taking account of this factor is of paramount importance. In research of Rezaiee Fard & Amiri (2024) used the NEO-FFI questionnaire to find personality patterns of software engineering and data science experts based on the Big Five personality traits: Neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness. Afterward, an ANFIS (Adaptive Network-Based Inference System) is conducted using the experts' personality data to match the participants of these fields with their corresponding choices. In Table 1 compare this research with the previous researchs:

Table 1.

Comparison with previous researchs

Row No	Authors	year	Research subject	Comparison with present research
1	Greco & Kraimer	2020	Goal-Setting in the Career Management Process: An Identity Theory Perspective	Research is in the field of career goal Using survey data collected at three points in time from 312 early career professionals. Neural networks are not used.
2	Hassan et al.	2022	Career Path Decisions and Sustainable Options	Recommends a holistic approach towards Career Path Guidance. this approach may be better executed using computer assisted systems. Neural networks are not used but Computer algorithms have been used for data analysis.
3	Sembiring et al.	2022	Effect Of Career Development and Work Motivation on Employee Performance with Job Satisfaction as	was conducted on 85 employees by using the Slovin formula sampling technique. The data collection technique used is

			Intervening Variable at PT. Mark Dynamic Medan	primary data in the form of questionnaires and secondary data obtained through documentation studies. The data analysis technique uses quantitative data which is processed with SPSS version 25. Neural networks are not used.
4	Xu & Flores	2023	A Process Model of Career Decision-Making and Adaptation Under Uncertainty	Using the dual-process theory of career decision-making (DTC), presented a model for the career path. Neural networks are not used.
5	Yadav et al.	2023	Career Prediction System using ANN MLP Classifier	career prediction using an Artificial Neural Network (ANN) Multi-Layer Perceptron (MLP) classifier. Fuzzy relationships are not used.
6	Kolhe	2023	Career Path Prediction System Using Supervised Learning Based on Users' Profile	this paper proposes an online career prediction system using supervised machine learning based on the user's profile. Fuzzy relationships are not used.
7	Song et al.	2024	Investigating machine learning's capacity to enhance the prediction of career choices	this study aims to enhance the accuracy of interest inventory-based career choice prediction through the application of ML. Using a large sample (N = 81,267) of employed and unemployed participants. determination of MF and FLS plays an important role in the results, which is not specified in this paper.
8	Bankins et al.	2024	Navigating career stages in the age of artificial intelligence: Asystematic interdisciplinary review and agenda for future research	illustrate how AI actively shapes individuals' career trajectories and we dissect these effects both within and across various career stages to situate AI within the broader context of careers research. The subject is discussed with a general point of view and the details are not specified.
9	siswipraptini et al.	2024	Personalized Career-Path Recommendation Model for Information Technology Students in Indonesia	presents a personalized career-path recommendation model (CPRM) to provide guidance and help college students choose information technology jobs The design of the CPRM is based on the personalized Naïve Bayes (p-

				NB) algorithm CPRM was implemented as a web-based Application. Neural networks are not used.
10	Rezaiee Fard & Amiri	2024	Decoding career success: A personality-based analysis of data science Professional based on ANFIS modeling	This study uses the NEO-FFI questionnaire to find personality patterns, Afterward, an ANFIS is conducted using the experts' personality data to match the participants of these fields. Questionnaire data has been used and ANFIS architecture has two inputs and one output.

the most career path models are based on the collection of questionnaire information and can be used at a certain time and place, these types of models need time and spending money to update those and does not have the necessary efficiency in situations where changes are rapid or new variables are introduced. It seems that having an intelligent model that has the ability to use large computer data as an input and quickly accept new variables and present the results makes the work of today's organizations very easy in analyzing and predicting the career path of employees.

In this research, after designing the model, a company in Tehran was studied and 21 data from its human resources were selected as inputs with the opinion of experts. First, human resources data were collected during 10 years from 2011 to 2020, and job categories were determined in 14 support categories and 14 operational categories for a total of 28 job categories. After clean data, a decision was made about the missing data, type and number of membership functions and interval of variables were determined, then the fuzzy neural network was trained so that 70% of the data was used for training and 30% of the data was used for testing.

In the end, the neural network was trained again using meta-heuristic algorithms SA, GA, ACO and the output error was checked. The algorithm that shows the least error is determined for the final model. Due to the fact that the input items of the model include various items, employees will quickly realize that the way they work will directly affect their career path, this will increase the effectiveness on the positive performance of the employees that automatically lead to increase in the productivity of human resource. The career model which is trained by the neuro-fuzzy network by using the Simulated Annealing algorithm is named abbreviation ASACPM (ANFIS Simulated Annealing Career Path Model).

The software which is used for modelling in this method is MATLAB software. The results of this research can be generalized to other companies and organizations. To use this model in other companies and organizations, the inputs of the neural network in the organization should be identified.

Literature Review

In today's large organizations, various variables affect the career path of an employee, in addition to this wide range and the large number of employees, it makes difficult to determine the appropriate model for the career path development with traditional methods, which can have harmful consequences such as reduced productivity, dissatisfaction and cause poor employee performance. The need of organizations for career path models that provide comprehensive analyze based on big data related to employees is felt more than in the past. Intelligent models based on neural networks are one of the new methods in this field. With today's digital age, the demand for labor is more dynamic than ever and the demand for job opportunities has increased.

One of the challenges facing organizations is how to place employees in the right job position. the results of one research show that the quality of human resources has a real effect on job performance, the quality of human resources has a real effect on employee loyalty, job performance has a real effect on employee loyalty (Darmawan et al., 2020). career path development is important model for employees in many risky businesses.

Determining the effect of leadership style and career development on employee performance has been done with the statistical analysis method so that leadership style and career development show a direct impact on employee performance (Suherman et al., 2022).

The dual-process theory of career decision-making resulted from a synthesized and critical reflection of career decision-making and related models in the contemporary psychosocial context of career development. The DTC features persistent decision uncertainty as a salient condition of contemporary career decision-making, and its theoretical framework and predictive model establish DTC's conceptual and empirical foundation, respectively (Xu & Flores., 2023). Companies can reduce career advancement procrastination (CAP) by helping employees curb their procrastination tendencies by reducing career barriers and increasing career resources, all of which should increase employee career self-efficacy (Zhu et al., 2023).

Today, the world is strongly merging into a single economic and cultural center, many people with busy and diverse schedules are seen in the global job market. As a result, people focus more on finding happiness and harmony in their work roles creating a relaxing career in order to find success in various job roles and performance is the most common approach of professionals around the world. The quantity and variety of fuzzy logic applications has increased dramatically in recent years. FL can accurately simulate nonlinear functions of any complexity (Rathnayake et al., 2022). There are many techniques for knowledge discovery such as decision tree, prior, clustering and neural network. Neural network (NN) techniques are used in many fields for nonlinear approximation. Statistical analysis and (NN) develop techniques to create models to analyze and predict certain dynamics. Kolhe et al. (2023) show an online career prediction system using supervised machine learning based on user profiles is proposed, which tries to create a model for the user and predict the career path in an accurate way It also provides practical feedback and career advice to encourage them to make meaningful career judgments.

Career development practices should support the development of individuals and the organization's requirements. Career development play a pivotal role in ensuring effective quality management (QM) (Els & Meyer, 2023). In focusing on concerns relating to the impact and acceptance of artificial intelligence (AI) integration in HRM are drawn insights from multidisciplinary theoretical lenses, such as AI-augmented and HRM(AI) assimilation processes, AI-mediated social exchange, and the judgment. (Rodgers et al., 2023). One of the technological trends that mark the era of digital transformation and significantly contributes to the development of digital competencies is Artificial intelligence (LLić et al., 2021). As artificial intelligence (AI) use expands within organizations, its influence is increasingly permeating careers and vocational domains. However, there is a notable lack of structured insights regarding AI's role in shaping individual career paths across career stages. implications of AI on careers, identify key barriers and enablers of AI use in this area, and reveal how the utilization of AI impacts individuals' career competencies, AI systems promote sustainable and equitable careers (Bankins et al., 2024).

Methodology

Fuzzy systems are examples of soft computations which are extensively used in different areas. In the recent years, a powerful system by using fuzzy inference system based on compatible neural networks have found many applications. This type of neural network use ANN and fuzzy systems for analyzing complicated relations. Today, fuzzy systems based on compatible neural system serve as one of the most effective methods in predicting the engineering systems models. The neural networks as well as ANFIS network hold the capability of modelling non-linear data (Jahangoshai et al., 2019).

The most important advantage in the fuzzy inference system is that it allows working with lingual rules. Nonetheless, the most important flaw of fuzzy inference systems is that those systems need the knowledge of a professional. In addition, these systems need a relatively long time to achieve proper membership functions. Approaches based on the neural networks or in more general term, the compatible systems based on learning process are able to remove this problem by improving the preliminary fuzzy inference systems. ANFIS or the adaptive neuro fuzzy inference system have created a class of compatible fuzzy inference by a hybrid of artificial neural networks and the fuzzy inference systems (Cabestany et al., 2011). ANFIS was introduced with Jang

(1993) in alignment with utilizing the advantages of artificial neural networks and the Sugeno fuzzy inference systems. In general, there are two fuzzy inference methods, namely, the Mamdani Fuzzy Inference Method and the Sugeno Method. The Mamdani method is an argumentized method which are mostly used for inference. Sugeno method was presented with Sugeno. This method is also known as a TS. The TS Fuzzy system benefits from the linear functions of entry variables as the results of the criteria. The Sugeno output function are either a line or a constant (Cabestany et al., 2011). One ordinary principle in a Sugeno Fuzzy model is in following form:

$$\mathrm{IF}(1 = \mathrm{x} \text{ and } 2 = \mathrm{y}) \Rightarrow \mathrm{z} = \mathrm{ax} + \mathrm{by} + \mathrm{c}$$

For a Sugeno model with zero rank the output level Z is constant $(a = b = 0)$. The output Z_i level for each principle has been weighed by the w_i firing power. As an example, for AND principle with entry $x = 1$ and the entry $y = 2$, the firing power is in following form:

$$\mathrm{W}_1 = (\mathrm{F}_1(\mathrm{x}), \mathrm{F}_2(\mathrm{x}))$$

In which, $F_{1,2}(0)$ are the membership functions for entries 1 and 2 (Jang, 1993). The final output of the system is the weighed mean of all the principal outputs which is calculated in following form:

$$\mathrm{Output} = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}$$

The ANFIS function is intensively attached to making a system with fuzzy logic, the type and number of membership functions that explain the entry variable of the fuzzy logic system and serve as the basis and essence of the laws (Wang et al., 2016; wang & shun, 2016). The most usual type of fuzzy inference system with the capability of being placed in a compatible network is fuzzy system Takagi-Sugeno (TS) the output of it is a linear function, and its parameters could be assessed by combining the least square methods and spreading error backward based on reducing gradient (Jang, 1993). In the ANFIS which is formed from five feedforward layer network, each node acts as a specific function on the entry signals. Assume this fuzzy inference system has “n” input and “k” output; and, for each entry variable, “m” lingual principle is considered as each i ϵ {1, 2,…,m} and each lingual principle could be shown with R_i then, the base of principle includes “n^m” Sugeno principle Which can be shown as follows:

$$\mathrm{IF}(\mathrm{X}_1 = \mathrm{A}_{i1}, \mathrm{X}_2 = \mathrm{A}_{i2}, \ldots, \mathrm{X}_m = \mathrm{A}_{im}) \Rightarrow \mathrm{Y}_i = \mathrm{W}_i$$

$$\mu_{ij} = e^{\frac{-(X_j - a_{ij})^2}{2b_{ij}^2}} \qquad \text{and} \qquad Y_i = \frac{\sum_{i=1}^{n} u_i w_i}{\sum_{i=1}^{n} u_i}$$

A_{ij} is a fuzzy complex for the i^{th} principle and j^{th} entry and a real number which indicates a part of the results. In the control system presented with Jang, the membership is presented as a Gaussian function (Cabestany et al., 2011). The structure of Neuro-fuzzy Network with 5 layers is shown in the Figure 1:

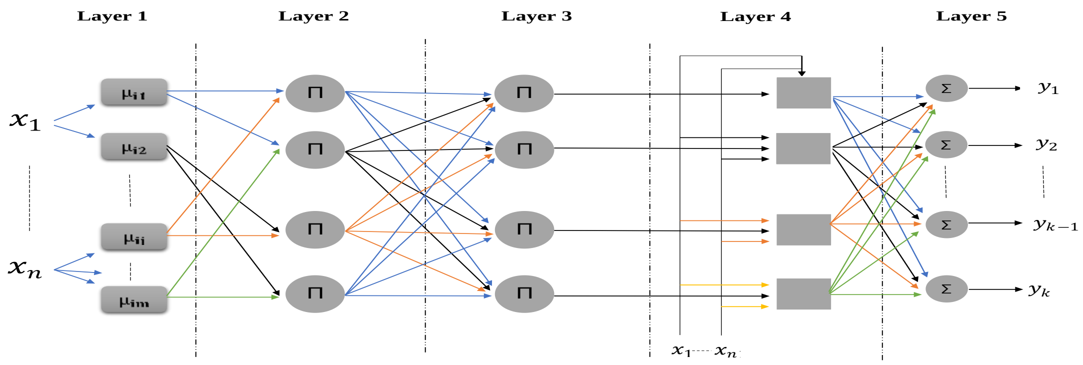

Figure 1. *Neuro-Fuzzy Network Architecture with N Inputs and K Outputs*

The first layer specifies the entry nodes by membership functions. In the second layer, each node specifies the activity degree of each law. The third layer normalizes the values of the previous layer, the fourth layer processes the output of the previous layer and the fifth layer calculates the final outputs. The training process in this system shows that non-linear parameters are used for the fuzzy membership functions in the first layer and the linear parameters are used in the fourth layer to compute the concerned output (Jahangoshai et al., 2019). By passing the entry parameters $X_1,\ldots,X_{21}$ from the neuro-fuzzy network specified the degree of staff's attachment to organizational jobs which is shown in percentage. The outputs which are the ranks of the organizational positions are divided into the column diagram template in 28 job categories and include $Y_1,\ldots,Y_{28}$ Job categories.

In this research, 70 percent of the data is used for training the network and 30 percent is used for the test.

The most widely used split ratios are 70:30; 80:20; 65:35; 60:40 etc., in which the sample size suits the nature of the problem. There is no fixed law for dividing training and trial datasets when it comes to data splitting. Some scholars have traditionally used the 70:30 ratio to differentiate the datasets. As most widely used in MATLAB, the training set and validation set by the 70:30 ratio (Kumar et al.,2022). In the neuro-fuzzy models, a compatible network, which is a general state of the multi-layer feedforward network, is utilized to solve the problem of identifying fuzzy inference systems parameters. A compatible network is a multi-layer feedforward structure the general output behavior of it is determined by the value of a series of correctable parameters. By using the compatible neural network, the main problem involved in using the fuzzy inference system; that is, the acquiring the fuzzy if-then laws and optimizing the parameters of the model, is removed.

Model Evaluation

Performance criteria are used to evaluate the effectiveness of predictive models. Each of these criteria evaluates the model in a specific way. These criteria are Mean Absolute Percentage Error (MAPE) (Bery, 2023):

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{x_{act}-x_{sim}}{x_{act}}\right| \times 100$$

And root mean square error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_{act}-x_{sim})^2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(x_{act}-x_{sim})^2}{\sum_{i=1}^{N}x_{sim}^2}$$

where N is the number of data vectors, x_{act} is the target value and x_{sim} is the predicted value in the proposed model, (Jahangoshai et al., 2019).

The ROC (receiver operating characteristic) curve is the true positive rate (TPR, equivalent sensitivity) versus the false positive rate (FPR, equivalent fall-out) of a classifier with variation the threshold. This method was initially started for the operators of military radar receivers in 1941. ROC analysis has emerged as an important tool in many fields, for example, medicine, Radiology, biometrics, meteorology, natural hazard prediction, and widely used in machine learning and artificial intelligence. A statistical measure related to area under the curve ROC which is AUC, is widely used to evaluate the performance of a classifier. Another closely related measure is called partial AUC, which refers to the AUC in a specific region limits the range of FPR and/or TPR. AUC is a more informative measure than accuracy for imbalanced data (Yang & Ying, 2022). AUC is the area under the ROK curve and the more its value is greater than 0.5 and closer to 1 the better (Maxwell et al., 2021; Muscheli, 2019).

Data Analysis

In this paper, the ANFIS architecture contains five layers and 28 outputs. O_i^j Shows the output of node "i" in layer "j". The nodes in first layer indicates the lingual variables, which are input variables the values of which have been determined by the fuzzy sets. Steps to build a career path model for employees based on human resource data are shown in the Figure 2:

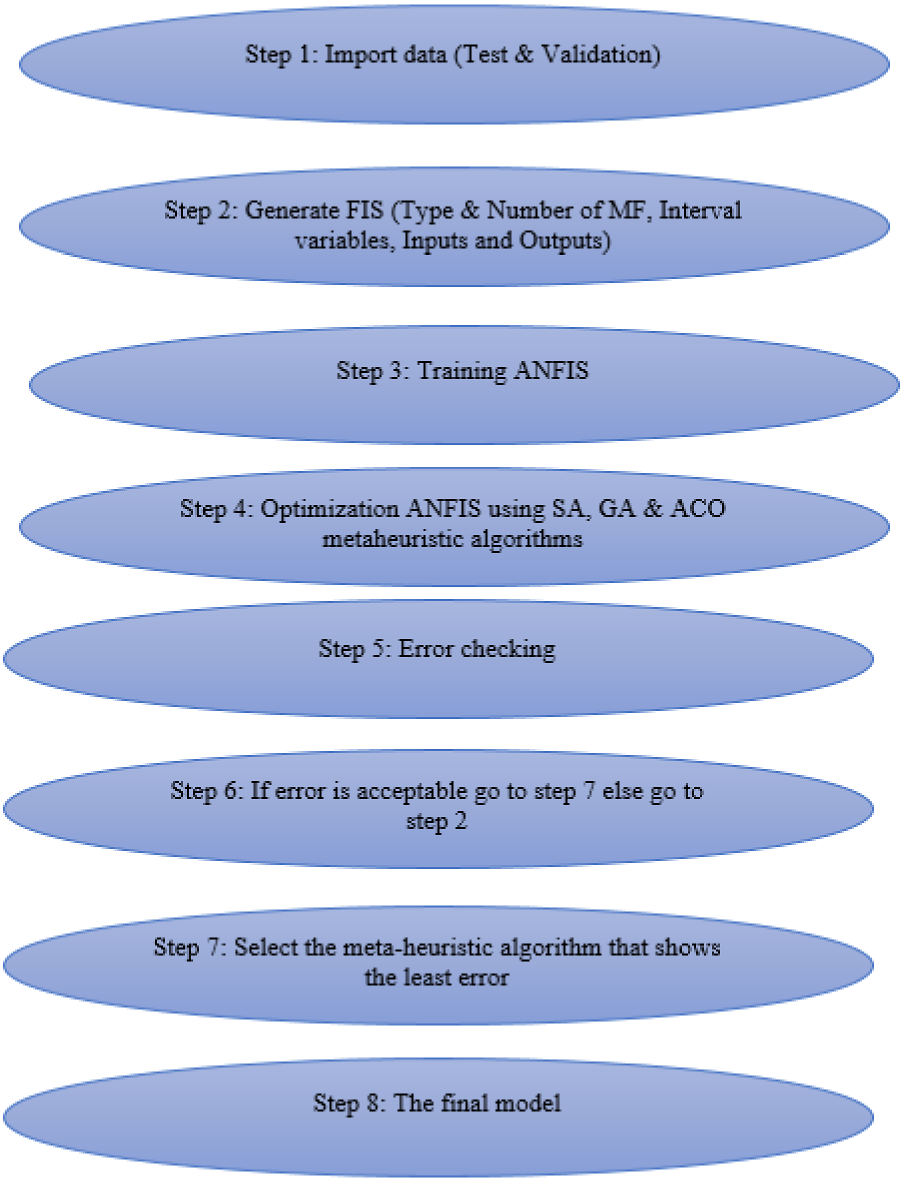

Figure 2. *Constructing the ANFIS Career Path Model diagram*

Each node in layer one is a compatible node and is defined by using the membership function of $\mu_{xj}(X_i)$ in which, (J= 1,2,3,4,5) shows the number of input variables in MF and I (I=1,2…,21) shows the number of input variables. MF has been presented by using the Gaussian curve with the two parameters of C (center of function) and σ (the width of the function).

Since the fuzzy laws are defined as: "If…. conditions, then…...results", the series of the input variables become quantified by using the fuzzy sets and are exhibited in the first layer nodes. The first layer consists of 21×5 components, which shows the MF of the input variables. The input variables are shown by using lingual variables which are explained in the fuzzy complex.

The output of the second layer is calculated as the lowest of the two input values:

$$O_i^2 = w_i = \mu_{A_i}(x_1) \times \mu_{B_i}(x_2)$$

Each "i" node in the third layer computes weights based on "i" law in the laws base:

$$O_i^3 = \overline{w_i} = \frac{w_i}{\sum_{i=1}^{n} w_i}, i = 1,2, \dots, n$$

In the fourth layer, in this research, ANFIS has more than one output, for each output variable we have separately:

$$O_{i(j)}^4 = y_{i(j)} = \overline{w_i} f_{i(j)} = \overline{w_i}\left(p_{i(j)}x + q_{i(j)}y + r_{i(j)}\right), j = 1, \dots, 5$$

Each 28 nodes in the fifth layer are those the nodes of its ANFIS output results have been computed ($Y_1,\dots,Y_{28}$). Each one of them is a fuzzy complex with specific amount of association with employees' career path. Now it is the time of defuzzification. removing the output values of ANFIS fuzzy mode could be carried out in different forms. In this paper, a method similar to the gravity center method is applied. Interval values ($Y_1,\dots,Y_{28}$) Crisp numbers range from zero to one hundred.

$$O_{i(j)}^5 = Y_1 = \sum_i y_{i(j)} = \sum_i \overline{w_i} f_{i(j)} = \sum_i \overline{w_i}\left(p_{i(j)}x + q_{i(j)}y + r_{i(j)}\right), j = 1, \dots, 5$$

The input and output couples are optimized by using the Fuzzy *C* mean clustering (FCM). This method is one of the most common clustering techniques in fuzzy systems modelling (Lukovac et al., 2017). The outputs can show different values. These values help us predict the path of career development and analyze the career path of employees with a very high quality. Some employees have the ability to achieve managerial jobs, but others can only work in clerical or expert jobs. There are 21 variables as input variables for each employee, but with the passage of time, the input variable changes and this change affects the output variable, Therefore, each employee can have more than 21 variables that are separated from each other. In order to determine exactly what method has been implemented for training, testing and receiving the output, in the form of the table below, we will check two employees named a and b. The display of variables has been avoided due to their personal nature and large volume.

This is shown in the table 2:

Table 2.

Sample inputs and corresponding outputs

Row No.	**employee**	**job categories**	**date**	**The corresponding output variable**	**X_1**	**X_2**	**…**	**X_{21}**
1	a	Support level 1	*	Y_1	*	*	…	*
2		Operational level 1	*	Y_2	*	*	…	*
⋮		⋮	*	⋮	*	*	…	*
i		level i	*	Yi	*	*	…	*
1	b	Support level 1	*	Y_1	*	*	…	*
2		Operational level 1	*	Y_2	*	*	…	*
⋮		⋮	*	⋮	*	*	…	*
j		level j	*	Yj	*	*	…	*

That: $i\&j \leq 28$

What has been done to train the neural network is that first 70% of the data, which are 70% of the rows of the entire table, are randomly selected, then the input data x1...X21 are set with the output variable of each row Yi, after this step, we ask ANFIS to predict the output values of the remaining 30% based on the input data. We continue this until the prediction error reaches the lowest value. Now ANFIS optimization is done using SA, GA and ACO meta-heuristic algorithms.

The output categories are shown in table 3:

Table 3.

Outputs obtained for two employees

Row No	Job categories	Outputs for two select employees	
		employee (a)	employee (b)
1	Support level 1	5	14
2	Operational level 1	4	15
3	Support level 2	6	8
4	Semi-operational level 2	5	9
5	operational level 2	4	9
6	Support level 3	8	22
7	Operational level 3	8	48
8	Only Support level 4	7	47
9	Support level 5	18	58
10	Operational level 5	15	66
11	Support level 6	25	75
12	Operational level 6	20	74
13	Support level 7	50	70
14	Operational level 7	40	69
15	Support level 8	55	55
16	Operational level 8	40	50
17	Support level 9	56	36
18	Operational level 9	41	40
19	Support level 10	58	25
20	Operational level 10	45	30
21	Support level 11	70	27
22	Operational level 11	55	29
23	Support level 12	72	31
24	Operational level 12	59	32
25	Support level 13	78	27
26	Operational level 13	57	28
27	Support level 14	89	26
28	Operational level 14	59	23

According to Figure 3, we find that the employee has the ability to be placed in support management jobs.

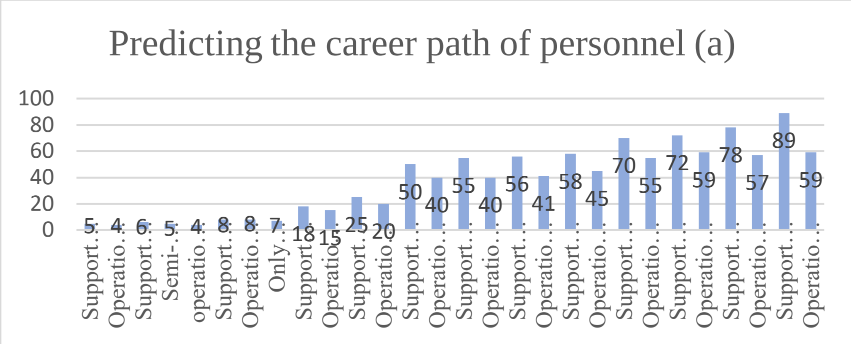

Figure 3. *predicting the career path of personnel a*

According to Figure 4, we come to the conclusion that it is better for the person to work as a technician.

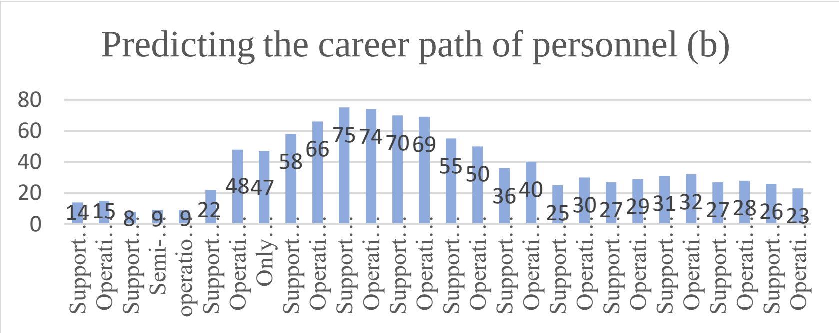

Figure 4. *predicting the career path of personnel b*

Results and Discussion

After collecting the company's human resources data, these data are divided into two categories, which include training data and test data. ANFIS function is checked on test data. 70% of the data was considered for training and 30% for testing. According to the human resources data of the studied company and after expert review, 21 items were selected as input variables of the ANFIS model in the career path of employees. These input variables can be determined in any organization according to the opinion of the experts of that organization.

Most papers that have conducted on the career path models were based on collecting questionnaires information and analysis by using statistical software; while in the present research, the career path of employees based on the human resources data of the ANFIS model has been determined by using MATLAB software. This method, along with the meta-heuristic algorithms which are employed could rapidly direct us to the model of employee's career path. The data of human resources in most organizations is kept in frame of information bank and modeling the career path of employees form those data makes the organization's work much easier than the traditional method. It should be noted that in each organization, depending on the type of activity and type of the existing data of human resources, it is possible to change the input variables. by using the input variables, ultimately, the model of employee's career path is computed by the help of SA meta-heuristic algorithm and are presented as outputs.

In the case study that has been done the ANFIS model of employee's career path has 28 outputs. to obtain the outputs, the entire jobs of the company divided into 28 job categories and ANFIS presents all 28 job categories along with a number that expresses in percentage per each job categories; and in this way, the career path model for each employee is determined. Each one of the job classes are considered in the two classes of 1- support and 2- operational; hence, in the uncertainty conditions, it could be possible to place the support personnel between different units of supports and operational personnel in different operational units in suitable career path. It is necessary to explain that in different situations, organizations can divide the support and operational personnel into different sub-categories and receive the final output of the model based on the required division, this feature of the present research model makes it possible for different organizations to use this model as needed. A three-dimensional view of the fuzzy neural network sensitivity during training is shown in the figure 5.

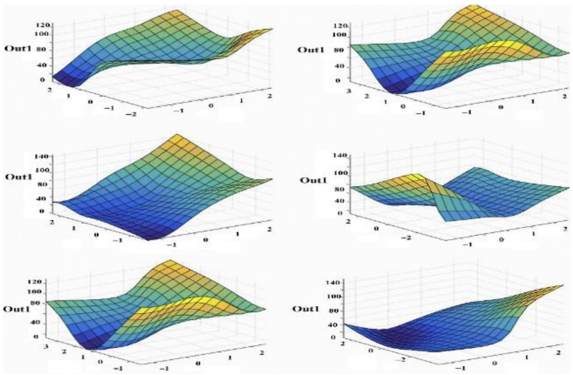

Figure 5. *fuzzy neural network sensitivity*

The SA algorithm was compared to GA and ACO algorithms and could show better results than GA and ACO algorithms. the SA algorithm needed shorter training time than GA and ACO algorithms. In addition, the error at the end of training time in SA algorithm was 0.222 while for GA algorithm, it was 0.239 and 0.297 for ACO algorithm.

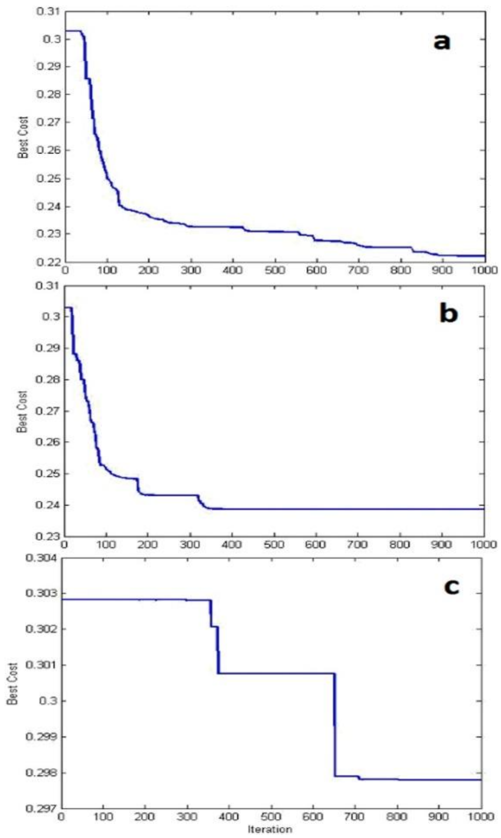

Figure 6. *Iteration and Error for SA(a), GA(b) and ACO(c) Meta-heuristic Algorithm*

ERROR.STD, MSE, RMSE and MAPE values in optimization by SA, GA and ACO algorithms are shown in the table 2. ERROR.STD is the standard deviation of the data generated from the test ERROR MEAN is a possible statement about the ratio of the sample size and the standard deviation of the sample. This index tries to measure the error of estimating the average of the statistical population by using the central limit theorem. ROC values and RF (Reference Factor) which is the average estimate of the criterion under consideration (Riley et al., 2020) are shown in the Figure 7:

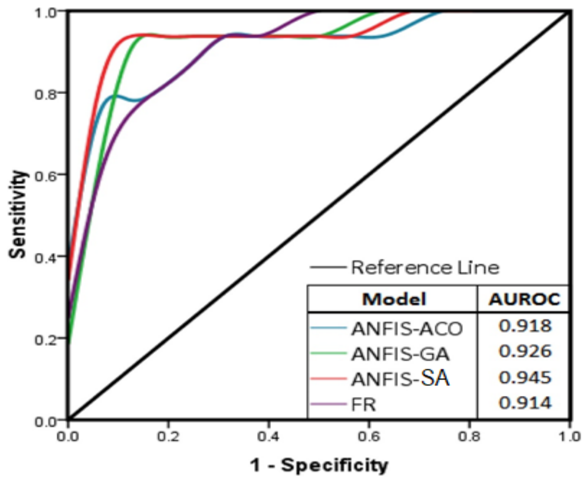

Figure 7. *AUROC Values and RF Sensitivity*

Data related to error and AUROC is presented in the table 4:

Table 4.

Results

no.	Model results	ERROR.STD	MSE	RMSE	AUROC
1	Neuro-fuzzy network optimized with SA meta-heuristic algorithm	0.198	0.0387	0.196	0.945
2	Neuro-fuzzy network optimized with GA meta-heuristic algorithm	0.255	0.064	0.254	0.926
3	Neuro-fuzzy network optimized with ACO meta-heuristic algorithm	0.3	0.088	0.297	0.918

Considering the training time and checking the error of ACO and GA methods, we come to the conclusion that the fuzzy neural network optimized with SA metaheuristic algorithm is a suitable method for analyzing the career path of employees. ANFIS presents information of membership degree of an employee in one of the 28 job categories; thus, it facilitates decision making .Even in conditions of uncertainty, organizations can manage their employees' career development path with the help of this model.

This model, facilitates managing the career path of employees in the organization. In fact, practical use of ANFIS career path model has direct impacts on the quality of managing the employees career path. ANFIS career path model is usable for all the organizations which maintain their human resources data in databank template; as it was noted, the human resources data were used as the input variables of ANFIS career path model.

An organization’s benefit from ANFIS career path model leads the human resources sections of that Organization predict plans for its future. This includes defining actions that should be taken for each job class of employees. As an example, for employees in Technician job class, factors such as horizontal displacement, educational plans and motivating incentive systems should be regulated. For employees in the job category of In-charge and Head, must be considered updating knowledge, presenting challenging work and substitutional programs; and for employees in the job category of In-charge, planning for education, supervision and job displacement shall be considered.

There are three theoretical implications put forth by this study. First, using the appropriate FLS and MF adjustment in the fuzzy neural network helped us to achieve the desired result and this is one of the important reasons for our use of neuro-fuzzy network for topics related to human resources, because Biron et al. (2021) show in human resources related topics, uncertainty and sudden changes in conditions can seriously challenge organizations but by using the neuro-fuzzy network, it is possible to make rapid changes according to the conditions. Due to the possibility of using neuro-fuzzy networks with the FLS feature, it is possible to consider the limits of uncertainty, and this leads to better prediction results.

The Gaussian membership function, is one of the famous and widely used membership functions. Another widely used membership functions we can mention sigmoid, exponential and linear membership functions (Babanezhad et al., 2021).

Second, the optimization of neuro-fuzzy network had been very useful to improve the results. in this research, we used the simulated annealing optimization algorithm and it was observed that it has better results than the two famous optimization algorithms GA and ACO. Also, according to Figure 8, the AUROC value calculated for the SA algorithm is 0.945, which is better than the values obtained for the GA and ACO algorithms.

Third, the evaluation of the model shows that the results are acceptable. Üstün et al. (2020) has expressed MSE and RMSE are indicators that show how has been successful the model. The MSE and RMSE values obtained for this model are shown in table 2.

Studies have confirmed that MSE and RMSE can be used to evaluate artificial intelligence models (Song & Wu, 2021; Üstün et al., 2020). Although in the research Abduljabbar et al. (2019) the performance of the GA algorithm was better than the SA algorithm and, in the research, Mohamadi and Moaddabi (2021) the performance of the ACO algorithm was better than the SA algorithm, but the research Amirteimoori and Kia (2022) confirms our findings about the better performance of SA meta-heuristic algorithm. Therefore, the impact of this research is revealed, which complements the previous findings and strengthens the view of intelligent models.

In this research, the career path of the employees of a company in Tehran has been intelligently analyzed and predicted and a model has been presented. The most important contribution is work on the process by which the extent of the influence of input variables on the career path of employees is determined.

Career path models that are presented based on questionnaire data have time and place limitations for application and need to spend significant time and manpower for localization but the smart model presented in this research has the ability to localize and quickly update based on human resources data. However, some limitations can also be stated for it, these limitations are divided into four parts: First, limitations of the model, although intelligent models have good predictive capabilities, those are based on the data receive as input. Due to the changes that happen in the real world, accurate prediction of what will happen in the future based on past data will be accompanied by an error.

in this research, we have tried to minimize the prediction error by using fuzzy concepts and the final decision of experts. Second, limitations and errors in the input data, the number and type of input data and their correct division have a direct effect on the calculations and output of the neuro-fuzzy network, If the input data has error, then the outputs will be far from the actual values. This concept is very important in cases where preliminary calculations or data separation are required before connecting the data to the neural network. Third, the limitation of choosing the type of neural network and the type of MF and defuzzification methods, because the outputs of the neural network are the result of the operations performed by the neural network on the input data. The structure designed for the neural network will have a direct effect on the output that is obtained, completely different outputs may be obtained with different structures. Fourth, the limitation of connecting to big data online, in order to accurately predict the model, any changes in the input variables need to be instantly injected into the system so that the neural network can perform the calculations and take into account the latest changes. One of the important reasons for our use of neuro-fuzzy network is to consider the conditions of uncertainty, however, it is possible to research other neural networks as well.

For future research, it is possible to investigate input variables such as the type, number and effect of variables on the model output. It is suggested to check the effect of each of the input variables on the career path independently. For example, how much has the variable of education or the variable of work experience been effective as a result of the predicted career path. we can also use the clustering feature of neural networks to properly divide the input data, the number and type of input and output data, then adjust the neural network based on the determined inputs and outputs. Another thing that can be done as further research is to change the structure of the model and compare the results with neuro-fuzzy model, we can also use the neural network inside a dynamic model to account for uncertainty in the dynamic model.

Conclusion

Career path analysis is a very important topic in the field of management because it has a great value for guiding the decision-making process in organizations and ultimately creating the productivity of human resources. So far, most of the work done in this field has been limited to questionnaire data and survey research, but in recent years, artificial intelligence technology has increased the development and redesign of human resources paradigms in different aspects, and in the meantime, the analysis of the career path is one of the most important topics. In this paper, by using the ANFIS neuro-fuzzy network, we presented a new method for determining the model of career path for the employees. Optimization of the model was carried out by using the metaheuristic GE, SA and ACO algorithms and the results were presented in each part. The traditional methods of determining the career path model of employees, which are often based on the collection of questionnaire information and the use of statistical software, are not very effective in today's advanced organizations that have a high rate of change; While the ANFIS model of employee career path, which is based on HR data, can be quickly implemented in any organization That keep information of its human resources in the framework of an information bank. accurately predicting career path trends still is an elusive goal, not only because the today business world is affected by policies, market environment, and market sentiment, but also because human resource data is inherently complex, noisy, and nonlinear. Recently, the rapid development of deep learning can make the classifiers more robust, which can be used to solve nonlinear problems.

In addition, this new method will be very efficient for analyzing the career path of employees in any organizations and particularly, organizations that face uncertainty in their human resources scope; for, as it has been noted, we divided the organizational jobs into the two classes of Support and Operational and this can make a significant contribution to replacing employees in the uncertainty conditions. Other applications of ANFIS model of the career path of employees is its capability of being used in the subjects related to the supply and demand of human forces as well as predicting the human forces.

The ANFIS model of the employee’s career path compared to other methods has this advantage of having the capability compatible by adjusting the fuzzy regulations based on the human recourses data of different organizations. This flexibility of the model makes us safe from computational limitations. In addition, as explained before, the ANFIS model of the employees’ career path is efficient in conditions we are facing uncertainty.

The ANFIS model of the career path of the employees could lead to change in traditional views and direct the today organizations to use new intelligent methods for analyzing and determining the career path of the employee by computer and databank of human resources. Of course, it is possible to conduct more researches in this field, including studying on the entry variables of the model as well as using other metaheuristic algorithms such as the algorithm of particle Swarm Optimization (PSO) and the algorithm of Tabu Search (TS) using various membership functions such as R, logistic and pseudo-exponential-like functions. in organizations where job categories are very scattered and these categories are not easily categorized, we can use neural networks clustering technique to determine these categories and then using the neural network prediction feature and Human resource data to predict the career path of employees.

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