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Neuro-Fuzzy Employee Ranking System in the Public Sector

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Abstract. One of the biggest problems the public sector faces is the proper utilization of human resources. Within a particular combination of practices, dynamic resource allocation management aims to increase employee productivity. The question that arises is how to match the abilities of employees on a measurable scale through their connection with the logic of neuro-fuzzy systems. Productivity and efficiency are two sides of the same coin and are directly related to the deployment of tasks. In this context, the new era of digital transformation along with the automation of processes allows the direct measurement of the workload status at any time. After the deployment of numerous experiments we verify that skill management is linked to performance measurement. Hard skills are selected since there is no direction of how to quantify soft skills and especially when applied to employees of a public body. ANFIS neuro-fuzzy system was selected since it uses the learning algorithm derived from neural network theory along with human criteria. Therefore the proposed system is based on two distinct factors, Skill management and Neuro-Fuzzy Inference System. The model initialization is system-data driven, which enhances the accuracy compared to traditional HR systems and secures a non-subjective procedure on employee management applied to the public sector.

Keywords. Skill Management, Public Sector, Neuro-fuzzy, ANFIS, Human Resources, Productivity, Ranking, Efficiency, Task Allocation, Personnel selection

1. Introduction

The public sector faces several problems, especially those related to the management of human resources. It has been adequately reported the lack of resource optimization especially in critical sections. As expectations due to the digital transformation are constantly increasing, it is observed that there is no mechanism for a holistic approach on controlling the utilization of human capital. In addition, a non-compliance culture which is found in the majority of the areas in public bodies seems to be one of the remaining

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issues that has been addressed without a proper solution so far [1]. The first results of a more precise observation, show a tendency for overloading public units without any plan for overcoming potential bottlenecks. In addition unusable human resources is the scourge of any public domain. The question that comes is how to define the capacity requirements of any department and under what circumstances any section is regarded as complete. Following our previous reasoning there is no exaggeration to say that lack of central management system is pushing the public sector to the brink of administrative and economic destruction. The traditional system of hiring and allocating resources is no more effective. The same applies for the evaluators on any "public structure". Hiring competent and skilled managers is definitely crucial and defines the main body of the public administration. This, in return, would require a detailed procedure which would include iq tests, along with personality and communication assessments [2]. Since decision making and leadership skills are highly appreciated, more attention should be paid on the competence skills, training, experience and diversity of managerial positions. It is noted that most of the evaluation reports contain mistakes. Bureaucracy still preserves inequalities among employees since there is no concrete base for performance appraisal. So how do we define productivity in the public sector? How do we assess the efficiency of human capital and the effectiveness of the services they provide? Productivity is a measure of economic performance that compares the amount of goods and services produced (output) with the amount of inputs used to produce those goods and services [3]. The more we increase output relative to input the more productivity increases. But in the case of services, quality should also be taken into consideration since only by producing more without a qualitative aspect could lead to low-level service [4]. The same applies when efficiency comes into the equation. The ratio of standard labor hours to the amount of time worked provides a metric of the effectiveness. It is now possible, through data analysis to forecast operational performance aiming at maximizing qualitative actions. Of course any policy formation in order to be effective needs to be assisted by a complete set of operations and not by some abstract statistical analysis.

Hence, in this work we propose an Integrated System for assessing the potential of each employee on the public sector which is based on the following properties:

- Skill management
- Neuro-Fuzzy Inference System

The key point is that the system is based completely on human independent efficiency assessment. In addition, the main critical factor is the time required for each task accomplishment. Tasks will be communicated through electronic protocol of public institutions. For the purpose of evaluation, the criteria selected should be in quantifiable and measurable terms.

2. Related Work

2.1. Overview

In section 2.2 the existing literature and related work are addressed. This section includes an outline in skill management with emphasis on hard skills. In section 2.3 relative deployment on neuro-fuzzy systems will be presented providing information on ANFIS.

HR evolution based on AI techniques is discussed as well as how tasks are allocated on the proposed HR management system.

2.2. Skill Management

As far as soft skills are concerned, change adaptability, communication and interpersonal skills, leadership as well as risk management are recommended in any business. A decision support system that could undoubtedly evaluate the candidates taking into account information such as psycho test results and interviews could provide a spherical result regarding the profile of each employee [5]. Although soft skills are referred to as vital in terms of employee efficiency, a major concern is that they cannot be quantified. How does anyone measure communication and leadership ability? Most of the approaches use a combination of mandatory and complementary factors in respect to overall human performance. Those include working experience, level of foreign language, university degree, analytical thinking of integrated systems, basic computer skill as well as organization, team-work, and flexibility [6]. So, class of degree, years of experience, professional certification as well as the age of each employee are indicators that inevitably affect the efficiency of every organization [7]. Each approach suggested an autonomous system with specific characteristics developed for job matching [8]. Certain findings indicated the importance of previous employment as the most important factor in the skill analysis equation [9]. Many researches have been conducted towards this direction, as well as using innovative techniques with the aid of social networks for profile analysis in personnel selection [10] . The authors in [11] indicated that a vital characteristic is the age of an employee, followed by experience. Some research based on experienced HR managers indicated the importance of education and especially a Master's degree as the most essential element and therefore giving maximum fuzzy weight value on the Fuzzy evaluation algorithm [12]. In all cases it was found that both Hard Skills and Soft Skills had a great influence on Employee Innovation Capability [13].

2.3. Neuro-Fuzzy Logic: ANFIS

Zadeh in 1965 introduced the mathematical logic for introducing imprecise data into problems that might have more than one solution. Calibration of vagueness is the essential element of this approach and the aim is to provide a systematic guideline to perform calculations based on linguistic terms and labels [14]. Fuzzy sets provided the methodology for producing the output of uncertainties by using linguistic quantifiers such as "High" "Low" e.t.c. But the evolution of the fuzzy sets is the neuro-fuzzy logic which combines the Artificial Neural Networks (ANN) with the fuzziness of the fuzzy sets. The authors in [15], in 2009, provided a neuro-fuzzy based agent that enables automating the processes of job requirements specification for applicant ranking in HR systems. ANN were deployed in order to diagnose the skill attributes and the corresponding weights in an automatic way, while fuzzy sets were used in order to express the uncertainties of each expert. So there is a combination of the artificial neural-network efficiency such as learning on large scale data-environments where the modeling of vague and unstructured knowledge can be achieved through fuzzy logic [16]. Such a system will be able to identify pros and cons of traditional HR management systems and rank potential employees based on their qualifications. What has to be highlighted is that the selection of the input is crucial for the performance of the algorithm. In all cases the neuro fuzzy modeling, based on NN logic, will identify the features that influence the selection procedure in respect to the weight factor of each input. Our model will be based on the adaptive neuro fuzzy inference system (ANFIS), first proposed in [17]. ANFIS deployees input/output data sets in order to formulate the system whose membership functions are adjusted by using the learning algorithm. The implemented Takagi Sugeno based Inference System will use the list of predefined skills of all employees of the data-target in order to rank them in terms of productivity.

3. Methodology

3.1. Employee Profile structuring

In order to have a detailed aspect of the fundamental parts of the profile structure, we design a four level factor profile. The employee profile will be updated on a frequent basis and in a period of time no more than 12 months. The requirements defined for each of the four sections are set according to international labor legislation and described below.

Academic skills such as seminars, bachelor degree, masters degree, school of public administration certificate and PhD - Working experience in the Public sector as well as last position of responsibility - Working experience in the private sector as well as last position of responsibility - and Age of each employee. In order to have a quantitative notion of the skill set, an employee profile matrix was deployed. Each section will hold distinct values based on the position of each skill. There will be a binary representation with a base of 2 for each position in the sections described above. Using this mechanism there is a unique arithmetic representation for every skill into a mathematical model. Vice versa, an arithmetic value uniquely identifies a specific set of skills. So in any case there is a forward-backward path which corresponds the skills of each section into a distinct mark. Those marks will initiate the feed forward procedure of our ANFIS system.

	EMPLOYEE PROFILE											
	1	2	4	8	16	32	64	128	256	512	1024	2048
K1	Academic skills								NOT USED			
	Seminar1	Seminar2	Seminar3	BSC1	BSC2	MSC1	N.S.P.A.	PhD				
	Fair					*Good*						
K2	Working Experience Public Sector (0-35 Years)						Responsibility			NOT USED		
	1	2	4	8	16	32	Head Small Dpt	Head Dept	Gen Mgr			
	Fair						*GOOD*					
K3	Working Experience Private Sector(0-35 Years)						Responsibility			NOT USED		
	1	2	4	8	16	32	Head Small Dpt	Head Dept	Gen Mgr			
	Fair						*GOOD*					
K4	Age (20-70 Years)											
	1	2	4	8	16	32	64	NOT USED				
	Fair (21-50 Yrs) - Enough (51-67 Yrs)											

Figure 1. Employee Profile Ranking

3.2. Task Categorization

According to empirical studies many tasks were initially identified for the public sector. But the focus is on the tasks that produce a valid and worthy outcome.In order to follow a general rule, tasks are categorized in terms of time duration taking into account the complexity of each one. This will be achieved by applying the same algorithm in order to discover the correlation between each Task Weight (TW), i.e TW_i and TW_{i+1}. So the interrelation between the tasks will be assigned and TW_0 will be referred to as the basis of all tasks with minimum impact on any employee productivity. $TW_5 = f(TW_4), TW_4 = f(TW_3), TW_3 = f(TW_2), TW_2 = f(TW_1), TW_1 = f(TW_0)$. Minimum Task Weight = TW_0. Following a form of interdependencies among tasks there is a general rule for every task TWi and TWj such as:

$$TW_i = \mathrm{f(TW_j)}\left\{\mathrm{i,j} > 0, \mathrm{TW_j} = \mathrm{a^*f(TW_0)}\right\} \tag{1}$$

3.3. Personnel Selection Criteria

A set of profile characteristics is selected which form the criteria for efficiency assessment of each employee. For the rest of the technical report each employee will be denoted as Node Ni. Input is the collection of skills of each employee. This collection will be based on Section 3.1 and will be obtained from the HR department of the public body and in accordance with the GDPR regulation.

- N = Set of All Nodes
- Ni = Node i

$$N_i \in N \tag{2}$$

$$N = \sum_{0}^{i} N_i, i = Employees_{Num} \tag{3}$$

3.4. Collect Time Statistics

Training data is collected through the electronic protocol of the public body for a time period of at least two (2) years. Therefore: TD_{min} = 2 Years For each N_i, the collected data is the time required to accomplish each TW_x which is called Time Factor. So there is an accumulated number of TW_x tasks and the mean time of TW_x per node N_i, for n samples, will be considered in order to avoid race conditions.

$$\overline{TF_i} = \frac{\sum_{i=0}^{n} TF_i}{n} \tag{4}$$

For simplicity reasons the mean value will be taken into consideration for the rest of the paper as TF_i. Since the overall performance is bound to TW_0, it is vital to identify TW_0.

$$\forall \mathrm{TWx} : \mathrm{TWx} = \mathrm{f(TW_0)} \tag{5}$$

Time Factor Zero = Time to accomplish Task TW_0,

$$\mathrm{TF_0} = \Delta\mathrm{tTW_0}, \mathrm{TF_x} = \Delta\mathrm{tTW_x} \tag{6}$$

Thus from: Eq. (4) + Eq. (5) + Eq. (6)

$$\rightarrow \forall \mathrm{TWx} : \mathrm{TFx} = \mathrm{f}(\mathrm{TF}_0) \tag{7}$$

Time Unit is defined as the minimum amount of time for task execution calculations.

$$\mathrm{TU} = 1 \text{ min} \Rightarrow \mathrm{TU}_{60} = 60\mathrm{mins} \tag{8}$$

In addition we introduce the term capacity actor which is the amount of TW0 tasks executed per Time Unit. Capacity Factor = ([Tw0] Tasks accomplished for each Node N_i per TU) where Time Unit (TU) is defined in (8) as 1 Minute.

$$CF_{Ni} = \frac{a \times TW_0}{TU}, a > 0 \Longrightarrow CFNi = \frac{f(TW_0)}{TU} \tag{9}$$

3.5. Comparison with Existing Approaches

The neuro fuzzy approach in the current research indicates that no human intervention is needed on order to adjust the initial data of the training data set. Employee evaluation and ranking has been detailed investigated and analyzed in recent bibliography [18],[19],[15]. In all cases the results were validated through extensive procedures but the subjectivity of the data due to selected output from human "experts" still resides in the equation. In our approach, continuous integration along with the nature of neural network capability, ensures that the proposed model will contain valid data directly from the system itself, thus providing a solid base for building a performance metric based on human productivity. If needed also the ranking decisions of each expert could well be in the input of the model, thus even challenging the scores from the supervisor of each employee.

3.6. Apply the ANFIS Algorithm

As far as performance measurement is concerned Root Mean Square Method(RMSE) will be preferred [20], along with gbellmf membership function [21]. Membership functions will be optimized by the use of hybrid algorithm compared to backpropagation due to low RMSE average value produced. Three stages will be used: data collection, development of a decision support system with ANFIS method and performance analysis. Input data for ANFIS system will be based on employee profile as discussed in 3.1. Therefore there are four sets as initial data that trigger the Fuzzy Inference System. For our model the following layers will be deployed:

- Layer 1 is the input layer (K1, K2, K3, K4) (Fig.1)
- Layer 2 describes the membership functions of each fuzzy input.
- Layer 3 is the inference layer
- Layer 4 performs normalization
- Layer 5 gives the output and
- Layer 6 is the defuzzification layer (Time Factor→ Capacity Factor)

4. Experimental Results

Training data consist of 108 records of employees in the whole region of the public sector of Western Greece, while testing data consists of 250 records, with profile data and the corresponding Time Factor (TF0) for each one. As stated on 3.4 the minimum period for data reception and analysis is set to two years. The basic skill set for admission in the public sector, as set by the National Law of Greece in our case scenario, is included in our research. Therefore, it is a four input–one output system with gbell shaped membership functions. K1 up to K4 will deploy 2 MFs due to limited sampling range. Rule list is presented on figures Fig.2 and Fig.3.

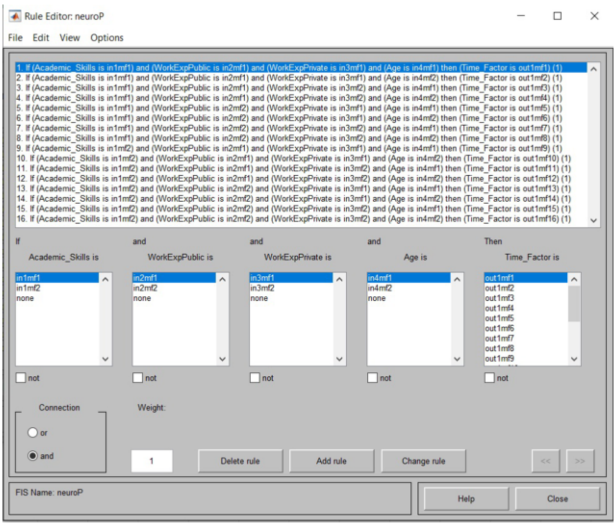

Figure 2. Rule Editor of ANFIS

Hybrid learning rule is selected for the model training. Evalfis graph on Fig.4 illustrates the deviation on data collected from the electronic protocol of the public body compared to those derived from fis evaluation and first analysis shows a tendency to approximate the results of our testing data.

Minimal RMSE was set on 9.3 Table. 1, on maximum 100 epochs, 104 parameters and 16 fuzzy rules, which indicates an acceptable Time Factor value compared to the data range of our records. We always have to keep in mind that the output illustrates human productivity and not precise time fractions of machine procedures. In any case more MFs and additional inputs are required, an additional set of data should be incorporated on next research.

The results could well be included into large scale public bodies aiming to spot bottlenecks due to mistaken decisions on employee categorization. On long term prospects with a minimum of five thousand samples the result would demonstrate not only the most valuable skill and asset of an employee but also the actions that need to take place in order to reconstruct the work hierarchy based on solid and efficient factors.

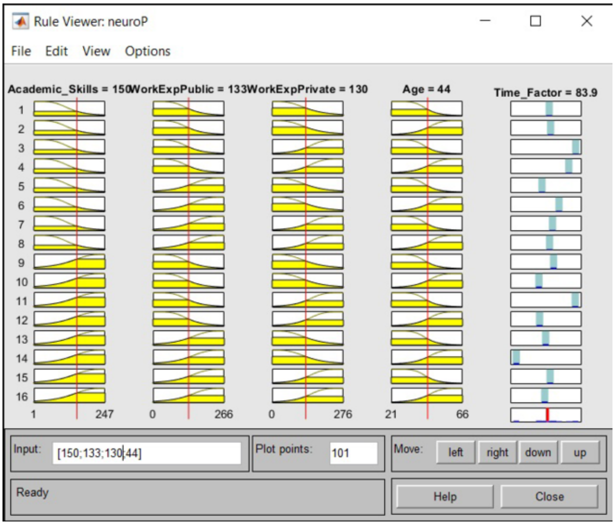

Figure 3. Rule Viewer of ANFIS

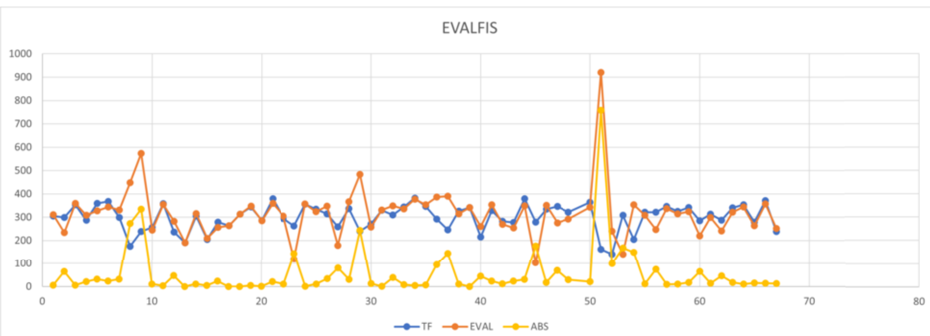

Figure 4. Evalfis deviation and evaluation

Table 1. ANFIS Info

Number of Nodes	55
Number of Linear Parameters	80
Number of nonlinear parameters	24
Total number of parameters	104
Number of training data pairs	108
Number of fuzzy rules	16
Minimal training RMSE	9.31153

5. Conclusions and Future Work

The results will form a unique employee profile structure that will mark the initiation of a new strategy in the employee ranking process. Quantification of skills along with predictability of employee productivity is a unique tool that the current proposal demonstrated by providing metrics for every employee in a public body. Future work includes services that would deploy mechanisms for task distribution and virtual employee assignment on an ad-hoc basis.

References

[1] Fourie D, Poggenpoel W. Public sector inefficiencies: Are we addressing the root causes? South African Journal of Accounting Research. 2017;31(3):169-80.

[2] Matjie T. The relationship between the leadership effectiveness and emotional competence of managers in the public sector. International Journal of Public Administration. 2018;41(15):1271-8.

[3] Dunleavy P. Public sector productivity: Measurement challenges, performance information and prospects for improvement. OECD Journal on Budgeting. 2017;17(1):1-28.

[4] Linna P, Pekkola S, Ukko J, Melkas H. Defining and measuring productivity in the public sector: managerial perceptions. International Journal of Public Sector Management. 2010.

[5] Verina W, Fauzi M, Nasari F, Tanjung DH, Iriani J. Decision support system for employee recruitment using multifactor evaluation process. In: 2018 6th International Conference on Cyber and IT Service Management (CITSM). IEEE; 2018. p. 1-4.

[6] Güngör Z, Serhadlıoğlu G, Kesen SE. A fuzzy AHP approach to personnel selection problem. Applied soft computing. 2009;9(2):641-6.

[7] Daramola JO, Oladipupo OO, Musa A. A fuzzy expert system (FES) tool for online personnel recruitments. International Journal of Business Information Systems. 2010;6(4):444-62.

[8] Chaikovska II. Economic-mathematical modelling of employee evaluation in the system of enterprise knowledge management. Actual problems of the economy. 2016;(9):417-28.

[9] Drigas A, Kouremenos S, Vrettos S, Vrettaros J, Kouremenos D. An expert system for job matching of the unemployed. Expert Systems with Applications. 2004;26(2):217-24.

[10] Melão N, Reis J. Social networks in personnel selection: profile features analyzed and issues faced by hiring professionals. Procedia Computer Science. 2021;181:42-50.

[11] Krichevsky M, Martunova J, Sirotkin V. Neuro-fuzzy recruitment system. Revista Espacios. 2017;38(62).

[12] Samalia V, Gumpy J, Manga I. Application of fuzzy logic for personnel selection. International Journal of Computer Applications. 2018;179(15):21-5.

[13] Sopa A, Asbari M, Purwanto A, Santoso PB, Mustofa DH, Maesaroh S, et al. Hard skills versus soft skills: which are more important for Indonesian employees innovation capability. International Journal of Control and Automation. 2020;13(2):156-75.

[14] Zadeh LA. Fuzzy sets. In: Fuzzy sets, fuzzy logic, and fuzzy systems: selected papers by Lotfi A Zadeh. World Scientific; 1996. p. 394-432.

[15] Doctor F, Hagras H, Roberts D, Callaghan V. A neuro-fuzzy based agent for group decision support in applicant ranking within human resources systems. In: 2009 IEEE International Conference on Fuzzy Systems. IEEE; 2009. p. 744-50.

[16] Zaheeruddin, Garima. A neuro-fuzzy approach for prediction of human work efficiency in noisy environment. Applied soft computing. 2006;6(3):283-94.

[17] Jang JS. ANFIS: adaptive-network-based fuzzy inference system. IEEE transactions on systems, man, and cybernetics. 1993;23(3):665-85.

[18] Amre Y, Ahmedabadwala M, Damania H. Decision Making Approach in Recruitment using Neuro-Fuzzy System. International Journal of Computer Applications. 2018;180:29-33.

[19] Ebrat M, Ghodsi R. Construction project risk assessment by using adaptive-network-based fuzzy inference system: An empirical study. KSCE Journal of Civil Engineering. 2014;18(5):1213-27.

[20] Lelavijit K, Kiattisin S. An Integrated Conceptual Model of 360-Degree Performance Appraisal and Candidate Forecasting Using Adaptive Neuro-Fuzzy Inference System. Journal of Mobile Multimedia. 2020:449-76.

[21] Solichin A, Saputri FH. An Adaptive Neuro-Fuzzy Inference System (ANFIS) Method for Recommending Employee Mutations in a Manufacturing Company. In: Journal of Physics: Conference Series. vol. 1908. IOP Publishing; 2021. p. 012016.