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Modelling and Analysis of Neuro Fuzzy Employee Ranking System in the Public Sector †

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Abstract: Human resource management has a significant influence on the performance of any public body. Employee classification and ranking are definitely time-consuming processes, which in many cases lead to controversial results. In addition, assessing employee efficiency through a variety of skills could lead to never-ending calculations and error-prone statistics. On the other hand, hard skill selection is proven to formulate a base for further investigation since subjectivity is not included in the performance equation. This research proposes a ranking model of employee selection based on certain criteria and attributes. The proposed prototype shows a series of results with a low error rate using ANFIS as the base methodology approach. This research was explanatory, and the population of this study consisted of employees with the majority of the sample in the wider region of Western Greece. The results showed a harmonic co-existence of the factors that proportionally affect the productivity of the employees in public service. Therefore, it provides the HR department with valuable information regarding the overall productivity of the public body, as well as significant material based on each profile separately. Therefore, efficiency was achieved through an automated time-saving procedure. The final output will enhance any personnel selection system with data extracted directly from the system, ensuring that the current method outperformed traditional approaches and secured 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

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1. Introduction

Selecting human resources with certain qualifications in order to enhance the ability of the public sector towards the direction of an optimal point of utilisation is the key factor to success. On the other hand, ranking the employees according to their capabilities will sustain the power of each organisation since the productivity and efficiency outcome will formulate the structure on which human resource departments will base the plan in their task allocation management system.

Therefore, the absence of a reliable central management system that could potentially extract and elicit valuable statistical information regarding the productivity of the employees in any public sector was the primary motivation of the current research. The traditional employee evaluation system has proven to be inadequate. The inevitable need for a domain expert with a flavour of "subjectivity" in the evaluation process could well be sidelined. Bureaucratic and obsolete HR procedures along with outdated tactics of personnel performance are driving the public administration to a dead-end, striving at the same time for new tactics without following the "current" of digital transformation of the present era. The need for an integrated system based on data records extracted from internal processes, which maintains performance indicators, is the next step of any HRMS. Existent research lacks a holistic approach to employee performance evaluation in the public sector, especially in relation to hard skills, which affect the overall efficiency of the services provided.

Therefore, following the innovative approach of the first system-initiated method of ranking employee performance based on the human profile and without the need for expert intervention, the current research provides not only an overall picture of the findings, but also demonstrates the validity and effectiveness of the proposed approach [1]. The initial approach to fuzzy set theory was proposed by Zadeh in [2], while the evolution into the combination of artificial neural networks and fuzzy logic principles was developed in the early 1990s based on the Takagi–Sugeno fuzzy inference system [3]. Therefore, the fuzzy inference system that was deployed was selected to be ANFIS, as more efficient one compared to the Mamdani and Sugeno approaches [4]. It has been documented that, for reasons concerning, the objectivity of the research, hard skills have primarily been selected in the fundamental case study of the model. The main reason lies in the fact that there is no approach that could incorporate soft skills, such as communication skills, critical thinking, teamwork, and leadership, or even intercultural interaction without being assessed by an expert's intervention [5]. Therefore, the selection of those factors does not provide reliable results for a long-term forecast. The fuzzy inference system was designed and tested in the Matlab environment, but the long-term goal was the adoption of an integrated system taking advantage of the interoperability with platforms that extract and analyse personnel-dedicated performance indicators. The set of rules was generated directly from the statistically processed reported data. The factors that were selected for the current research were set by the National Law of Greece (Law 3528/2007) (available at: https://www.ilo.org/dyn/natlex/natlex4.detail?p_lang=en&p_isn=81308, accessed on 30 January 2023) and provide the base for admission, as well as the criteria for selecting employees for positions of responsibility in any public service. Therefore, those factors that were selected as inputs for the proposed system were the following: academic skills, work experience including the position of responsibility in the public sector, work experience in the private sector along with the corresponding position of responsibility, and finally, the age of each employee. The first results showed an inextricable connection between all inputs of the model and the corresponding measurements of time execution per task for each employee [1].

The main purpose of the article was to establish practices for assessing the productivity and efficiency of employees with an automated procedure that could lead to a generic framework for a ranking system for human capital in public administration. The article is organised as follows: Section 2 presents related work and contributions, and Section 3 introduces the research methodology. The results are presented in Section 4, followed by a discussion and the conclusion in Section 6.

2. Related Work and Contributions

The personnel selection and ranking problem have been extensively reported in the recent literature. Compared to the public sector, the private sector has been more concerned with and enthusiastic about adopting a technology-driven human resources function in every organisation, and the focus has been on cost optimisation, system and process efficiency, and the timely performing of business partnering functions as the management objective for securing strategic advantages, in order to secure the survival of each business [6]. Heading towards the era of digital transformation, the public sector cannot remain impassive, and it is imperative that the private sector's philosophy be followed. Social security, insurance, and appropriate working conditions are some of the motivating means in the public sector [7]. The academic level, work knowledge, work skills, work experience, and age were selected among a multitude of skills from a multicriteria selection model for employee selection [8]. In a similar case for personnel selection in IT companies, decision-making, familiarisation with IT technology, as well as professional experience and educational background have been considered as main factors for every proposed decision model [9], while personality traits and foreign languages have been proposed as fundamental criteria for logistics management based on a hybrid AHP TOPSIS approach in order to define the selection criteria weights and rank the alternatives [10]. In a more generic approach, management support, organisational climate, job environment, adaptability, and intrinsic motivation play a vital role in determining employee performance [11], while recommendation letters and IQ tests are considered as crucial inputs for the decisions of every HR department regarding employee admission [12]. The initial approach was performed on the vague and unstructured knowledge of personnel skills and capabilities included the adoption of fuzzy decision-making and the corresponding procedure in order to determine the most-suitable candidate for personnel selection [13]. Following the same pattern, a pure fuzzy model for competency-based employee evaluation and selection was introduced by Golec and Kahya (2006) by deploying a comprehensive hierarchical structure, consistent with organisational goals and strategies [14].

However, the lack of a generalised method for determining the weight of each factor in a classification procedure has led to the adoption of neural networks in fuzzy sets, where the importance of each skill is extracted, based on the strength of related links in the trained neural network. The ranking algorithm based on a candidate's CV through an automated process has always been a need of any HR department, and such a proposed scheme could make use of a neuro fuzzy system [15]. The impact of neuro fuzzy systems in business has been documented with extended deployment in finance and marketing. With respect to human resource management, the production of a fair and consistent resume ranking policy has always been the ultimate goal considering also the performance evaluation of the employees of an organisation [16].

The soft skill evaluation of the employment of personnel holding a Ph.D. has been analysed, leading to valuable information regarding strategic decisions by the HR department. The results showed that the neuro fuzzy approach was able to more accurately represent the HR department's reasoning when assessing profiles was required, compared to the Mamdani approach. The system was able to select from a pool of candidates those that better fulfilled the set of predefined HR manager requirements. The outcome was illustrated as a vector representation of profiles with flexibility in adaptations when required [17]. In similar research for the employee selection process in child daycare, the proposed system was able to provide the decision with an error rate of 0.00016 based on both observations and interviews. This supported the idea of a hybrid system that, using ANFIS, could give the right recommendation for the employee selection process [18].

ANFIS was in many cases selected in terms of efficiency among neuro fuzzy inference systems as a decision support system for candidate classification in the employment process [19]. The target ANFIS hybrid model was proposed for the objective classification of candidates during the employment process of recruiting personnel in companies in the field of information technology. Optical Character Recognition (OCR) was deployed in order to extract metadata (attributes) available in these documents for subsequent analysis through ANFIS [19]. Employee performance evaluation was also approached in terms of neuro fuzzy logic by Escolar-Jimenez [20], providing valuable information regarding the objectivity and transparency of the process. Huynh et al. [21] demonstrated the robustness of ANFIS in order to meet the optimum design for magnification mechanisms while a bi-algorithm with pure fuzzy logic and ANFIS was followed for the optimisation of compliant gripper mechanism design [22]. In research conducted by Kannathal et al. [23], ANFIS was also selected, in order to rank the abnormalities of six-hundred records for ten different classes of cardiac states. Although the accuracy was subject to the size of the training set, it was highlighted that, using a three-input system with a bell-shaped membership function, the adaptive neuro fuzzy inference system showed better results in terms of efficiency compared to a pure Artificial Neural Network (ANN) method. A similar, but quite novel approach combined the use of neuro fuzzy networks with IoT services, in order to evaluate the performance of employees. The activities were traced using Radio-Frequency Identifiers (RFIDs) for a total of fifty data records, while ANFIS was deployed for learning and automated decision optimisation. The accuracy rate almost reached 95% with an RMSE of 0.0717, thus leading to a unique proposed model for real-time tracking of jobs, outperforming techniques using ANNs [24]. In similar algorithms of fuzzy inference systems, the factors selected for applicants' evaluation and ranking, using the Mamdani approach in the HR department, included: education, language, job experience, and teamwork ability among many others. The output provided sufficient information regarding the quality of the selected personnel [12]. Güneri et al. [25] suggested the ANFIS selection model for the supplier selection problem. Factors that influence the final choice, such as quality and cost, were filtered through the Adaptive Neuro-Fuzzy Inference System (ANFIS) in order to overcome the supplier selection dilemma. The approach showed exceptional performance compared to multiple linear regression, even when new criteria were added to the algorithm [25].

ANFIS was also selected as the main method for recommending employee mutations in manufacturing companies [26], while a quite remarkable approach demonstrated an optimisation method of a queuing system in warehouses. The study referred to the simulation of a queuing system in a logistics company where ANFIS was introduced for modelling the time component of the system as the criterion for optimisation. This could well be incorporated into later stages of the current research since task management and job allocation will be thoroughly discussed in the next sections [27].

A more comprehensive approach that takes full advantage of hesitant fuzzy sets and multi-granulation rough sets was introduced in [28], which provides human resource managers with more flexible access to convey their understanding of the recruitment knowledge base. Additionally, the work in [29] proposed a hybrid model named adjustable HFL MG-DTRSs over two universes, which provides a new perspective by depicting the subjective and hesitant opinions of decision-makers by utilising multiple linguistic terms.

A recent study of 29 papers revealed a set of ten factors that influence the design of performance measurement systems in public administration and categorised them into three groups: factors related to purposes such as social approach, factors related to stakeholders such as accountability, and factors related to management such as effectiveness and efficiency [30]. The production capability of human capital was considered to be one of the most-valuable assets even at universities, selecting four factors for the evaluation: level of education, experience, work satisfaction, as well as abilities [31]. What is important from every aspect of the research conducted so far is that the personnel assessment does not act as a punitive measure, but rather as a best practice empowering the employees' trust [32], since the ultimate goal is to further engage them in public administration services [33].

In the study [29], the authors proposed a three-way decision model for employee performance evaluation, which considered the opinions of multiple stakeholders, such as managers, peers, and subordinates. The model integrates the opinions of each stakeholder through a combination of decision rules and fuzzy reasoning to produce a final evaluation of each employee's performance. The authors evaluated the proposed model on a real-world dataset and showed that it outperformed traditional two-way decision models in terms of accuracy and consistency.

These studies demonstrated the importance of incorporating advanced computational techniques in the development of employee ranking systems. By leveraging the strengths of granular computing and three-way decision models, organisations can gain a more comprehensive and accurate understanding of employee performance and make informed decisions about their workforce. However, it is important to note that these systems are not a replacement for human judgement, but rather, a tool to support and improve the performance evaluation process.

Ultimately, we drew upon previous works we have already discussed [34–38]. These works provide a foundation for the current study, as they address various aspects of machine learning and decision-making, which are essential components of the system that is proposed. By incorporating the insights and methods presented in these prior works, this study aimed to contribute to the advancement of the field.

3. Methodology

3.1. ANFIS

It has been reported that the majority of the cases related to multi-attribute decision-making are characterised by a definite degree of vagueness. Therefore, research on MADM and MCDM, respectively, incorporates models for dealing with this level of uncertainty such as fuzzy sets and fuzzy logic as a more generalised approach. Eliminating this unpredictability was the main goal of the approach, followed by a targeted calibration of the model's vagueness. Current research has determined that the ANFIS algorithm can be used in multi-criteria decision-making problems for supplier evaluation and selection with more precise and reliable results [39].

Based on Jang (1993) [3], ANFIS consists of five distinct layers, and the mathematical concept is explained as follows. For simplicity reasons, only two inputs were considered:

- Layer 1: In the fuzzification layer, every node i in this layer is a square node with a node function:

$$O_i^1 = u_{A_i}(x) \tag{1}$$

  where x is the input to node i, A_i is the linguistic label, and O_i^1 is the membership function of A_i.
- Layer 2: Circle nodes in the normalisation layer multiply the incoming signals and send the product out. This represents the firing strength of a rule.

$$w_i = u_{A_i}(x)u_{B_i}(y), i = 1, 2 \tag{2}$$

- Layer 3: Every node in this layer, labelled in Figure 1 with N, calculates the average ratio of the ith rule's firing strength.

$$\bar{w} = \frac{w_i}{w_1 + w_2} \text{ or in a generic form: } O_i^3 = \bar{w}_i = \frac{w_i}{\sum_{i=1}^{n} w_i}, i = 1, \ldots, n \tag{3}$$

- Layer 4: Every node "i" in this layer is a square node with a node function, where w_i is the normalised firing strength from the output of Layer 3 and p_i, q_i, r_i are referred to as consequent parameters.
- Layer 5: The final layer represents the overall output y of the network as the summation of all incoming signals:

$$O_i^5 = f = \sum_i \bar{w}_l f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{4}$$

  where O_i^5 is the output of the i^{th} node in Layer 5, $\bar{w}_i$ is the normalised firing strength of the i^{th} rule calculated in Layer 3, and f_i is the output of the i^{th} node in Layer 4, which is given by the product of the normalised firing strength and the consequent parameters p_i, q_i, and r_i. The overall output of the system is the summation of the incoming signals from all the nodes in Layer 4. The output of the ANFIS network in its final form can be expressed as follows:

$$f = \frac{\sum_{i=1}^{n} w_i(p_i x + q_i y + r_i)}{\sum_{i=1}^{n} w_i} \tag{5}$$

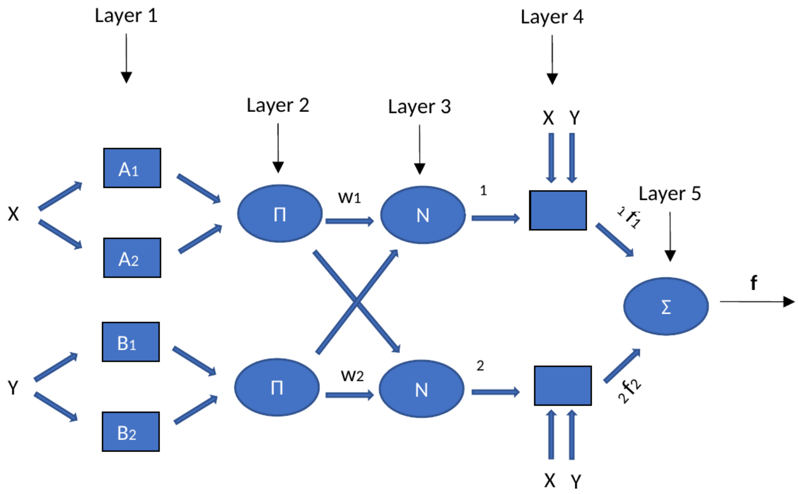

Figure 1. Two-input structure of ANFIS.

3.2. Workflow

There are five distinct phases for acquiring the capacity factor for each profile of the given dataset as seen in Figure 2. In the first phase, the synthesis of the generic profile structure takes place. Then, the tasks are categorised according to their complexity, leading to the establishment of a relationship among them in terms of time execution. In the third phase, the personnel criteria are set, thus forming the subset of eligible employees according to the predefined criteria. Time statistics are then collected for a valid period of time, and finally, the ANFIS algorithm is applied, providing a logical transformation of the profile into task execution time, defined as the time factor.

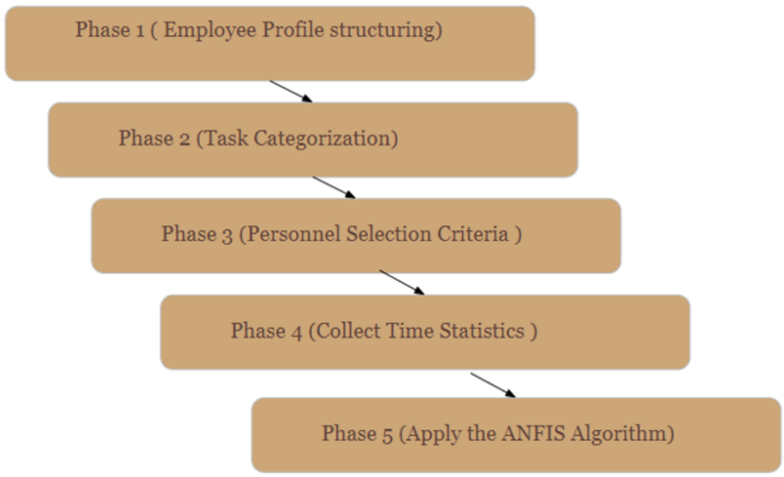

Figure 2. Workflow phase of the system.

3.3. Data Preparation

Michalopoulos et al. [1] deployed a four-level factor profile. The skill set was based on Decision No. 540/2021 of the Greek Council of State according to Council Directive 90/270/EEC:

- K1: (academic skills):
  1. The number of seminars related to the current work with a maximum of three (S_1, S_2, S_3).
  2. The number of Bachelor's degrees with a maximum of two (B_1, B_2).
  3. The availability of Master's degrees.
  4. Certification from the National School of Public Administration.
  5. A Ph.D. diploma.

- K2: (work experience in the public sector):
  1. Number of years with a maximum number of 35.
  2. Type of responsibility.
  3. Head of a small department.
  4. Head of the department.
  5. General manager.
- K3: (work experience in the private sector):
  1. Number of years with a maximum number of 35.
  2. Type of responsibility.
  3. Head of a small department.
  4. Head of department.
  5. General manager.
- K4: (age):
  1. Number of years with a range of (20–67). Greek legislation sets the age of 67 years as the limit when working in the public sector.

3.4. Measuring Time

All tasks were distributed through the central protocol of the public body. When a task id TID_k is assigned to user P_j, the corresponding timer is triggered. There were two main cases thereafter. In the first one, the task was completed by user P_j and archived or forwarded, corresponding to time T_{ij}. In the second scenario, user P_j was continuously reassigned the same task as long as this was not considered as finished by the local supervisor. Timer T_{ij} is now the summation of all timers, thus giving a total amount of time for every profile P_j on any given task k:

$$TF_{PjTk} = \sum_{i=0}^{n} T_{ijk}\ ,\ \ i, j, k,\ n > 0 \tag{6}$$

which is defined as the time factor.

Therefore, tasks are literally "jobs" assigned by each supervisor to the designated employees and are communicated electronically through the network of the public body with a distinct timestamp each time it is passing through each node Ni, as seen in Figure 3. Through the lens of the digitisation era, most of the public administration services have adopted the use of electronic document management along with task dissemination. Such information is protected by the GDPR and is kept internally in the database of each public body in an encrypted format. As data will migrate to G-Cloud for all governmental services, it is evident that data security and integrity are ensured.

3.5. Defining the Tasks in Public Organisations

Although there is no specific list of assignments that are deployed in the public sector, nevertheless, each department processes tasks related to its field. For the purposes of the current research, the following primary tasks in the areas of interest were identified. These are shown in Table 1.

Table 1. Public body tasks.

Financial Request	Technical Opinion
Suggestion of new technical document	Draft tender design
Committee minutes	Design of a national tender
Primary expense claim	Design of an international tender
Contract deployment	Implementation of a proposal for inclusion in the NSRF

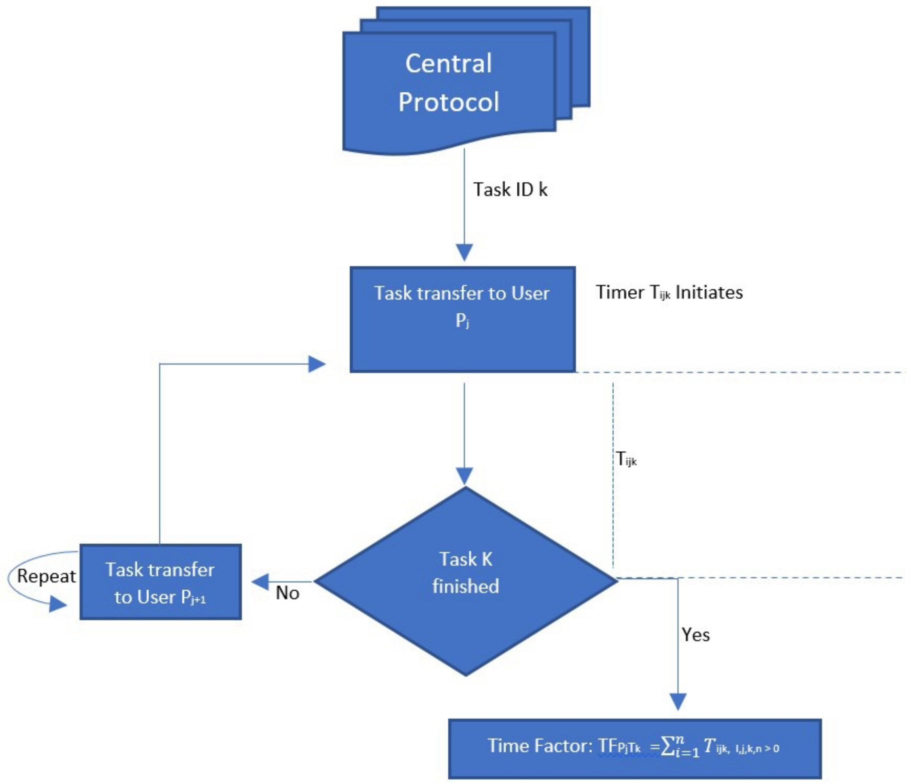

Figure 3. Measuring time.

As can be clearly identified from the list above, the empirical observation identified tasks that produce value. Time-limited procedures such as the signing of documents by a unit manager do not fit in the structure above since, no matter the profile of each user, in many cases, there is no need for special skills in order to accomplish such an action, which could lead to misleading results. Therefore, in our case, designing a non-electronic draft tender led to a time-factor TF_{PjTk}, while the electronic national tender to TF_{PjTk+1} for each profile P_j. TF_{PjT1} indicates the task with the minimum time duration, which is the completion of a financial request. The following table indicates the time (in minutes) for a non-electronic (T_k) and electronic tender (T_{k+1}), respectively, based on 15 different samples of profiles.

It must be noted that, for our case above, a tender cannot be deployed by non-related profiles.

P = Set of all profiles in the public sector.

A = Set of all areas of interest (e.g., procurements, finance, informatics, logistics, tourism) in the public sector.

Therefore, $A_{procurement} \subseteq A$, and the corresponding profiles specialised for procurement jobs follow the same pattern: $P_{procurement} \subseteq P$.

As seen in Table 2, the mean time for TF_{PjTk} is 180 min and for TF_{PjTk+1} is 816 min, thus resulting in the ratio:

$$\frac{TF_{PjTk}}{TF_{PjTk+1}} = 4.52 \tag{7}$$

Table 2. Time-factor table.

Sample No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
TF_{PjTk} (min)	149	106	81	319	209	157	208	171	129	138	180	338	197	208	115
TF_{PjTk+1} (min)	1049	1185	1090	739	900	946	1047	396	909	571	771	734	460	823	623
TF_{PjT1} (min)	53	74	47	25	21	29	31	44	66	46	54	86	43	63	42

The standard deviation of TF_{PjTk} is 69.4 compared to 226 for TF_{PjTk+1}, respectively. For the simplest task, which is a financial request, the mean time for TF_{PjT1} is 48 min with a standard deviation of 17.6 min.

In order to establish a correlation among the list of tasks, a task weight TW_x is assigned to each and every "job" undertaken by the employees. Following the general rule of [1], for every task TID_i and TID_j, there is always a dependency between them, which follows the rule:

$$TWi = f(TWj)i, j, > 0 \tag{8}$$

TW_1 is the minimum task weight upon which the tasks will be related. Therefore, TW_1 and TW_i also follow the same relation:

$$TWi = f(TW1)i > 0 \tag{9}$$

As discussed in Section 3.4, statistical information is extracted through the electronic protocol of each public body. The average time-factor for all profiles P_j, per TID_i, was calculated and recorded through the system. Even at this stage, the expert's intervention could provide an inaccurate correlation among the TID_s. Therefore, for instance, for TID_1 and TID_2,

$$\mathrm{TFPjT_1} = \frac{\sum_{j=1}^{n} TID_{j,1}}{n} \quad \text{and } \mathrm{TFPT_2} = \frac{\sum_{j=1}^{n} TID_{j,2}}{n} \tag{10}$$

For reasons of the comparability of the task weights, the values above were normalised.

From Equations (6), (8), and (9) and taking into consideration that a financial request has a task weight of TW_1, we constructed the following relationship table.

Therefore, the task weights denote the amount of effort, in terms of time, needed to complete the assigned job compared to TW_1. Therefore, as seen in Table 3 for instance, designing an international tender requires 25-times more effort compared to any TK task assigned with the TW_1 weight in order to be accomplished.

$$TW_{international\_tender} = \mathrm{f}(\mathrm{TW}_1) \Rightarrow TW_{international\_tender} = 25TW_1.$$

The aforementioned defined time unit is one (1) minute, and this is considered the minimum amount of time for task execution calculations.

$$\mathrm{TU} = 1 \text{ min} \Rightarrow \mathrm{TU}_{60} = 60 \text{ min} \tag{11}$$

Table 3. Relationship table.

Task ID	Task Weight	Task	Task ID	Task Weight	Task
1	1	Financial request	6	8	Technical opinion
2	2	Suggestion of new technical document	7	3.75	Draft tender design
3	30	Committee minutes	8	17	Design of a national tender
4	1.2	Primary expense claim	9	25	Design of an international tender
5	2	Contract deployment	10	12	Design of a proposal for the NSRF

3.6. Assessment of Employee Quality

In order to assess employee quality, the term capacity factor has been introduced [1]. Each employee is denoted as N_i (node N_i) such that

$$\mathrm{N} = \text{ Set of all Nodes} \tag{12}$$

$$\text{Node Ni} \in \mathrm{N} \tag{13}$$

Therefore,

$$\mathrm{CF_{NI}} = \frac{TU \cdot TW_{NI}}{TF_{NI}} = \frac{TU \cdot a \cdot TW_1}{TF_{NI}}, a > 0 \tag{14}$$

In addition, we took into consideration the fact that the efficiency of each employee is dependent on the factors described in Figure 4, which are education, work experience, age, and position of responsibility. Therefore,

$$\mathrm{CF_N} = \mathrm{f}(\mathrm{K1},\ \mathrm{K2},\ \mathrm{K3},\ \mathrm{K4}) \Rightarrow \mathrm{f}(\mathrm{K1},\ \mathrm{K2},\ \mathrm{K3},\ \mathrm{K4}) = \frac{TU \cdot a \cdot TW_1}{TF_{NI}}, a > 0 \tag{15}$$

EMPLOYEE PROFILE											
Binary Range	1	2	4	8	16	32	64	128	256	512	1024
Factors											
	Academic Skills										
K1	Seminar1	Seminar2	Seminar3	B1	B2	M1	N.S.P.A.	PhD	NOT USED		
	Working Experience Public Sector (0-35 Years)						Responsibility				
K2	1	2	4	8	16	32	Head Small Dpt	Head Dept	Gen Mgr	NOT USED	
	Working Experience Private Sector(0-35 Years)						Responsibility				
K3	1	2	4	8	16	32	Head Small Dpt	Head Dept	Gen Mgr	NOT USED	
	Age (20-70 Years)										
K4	1	2	4	8	16	32	64	NOT USED			

Figure 4. Profile structure.

From Equation (15), it becomes clear that all factors (K1 up to K4) influence at different levels the number of tasks per time unit in each profile.

4. Experimental Results

The data records were filtered before being used in order to develop a fuzzy system using the MATLAB software. According to the performance indicators, the gbellmf membership function with the use of a hybrid algorithm was selected due to low root-mean-squared error, thus providing a four-input, one-output system as illustrated in Figure 5. K1 up to K4 were deployed as the input data for the ANFIS system, as discussed in Section 3.3, and each node executed a specific functionality for every input provided.

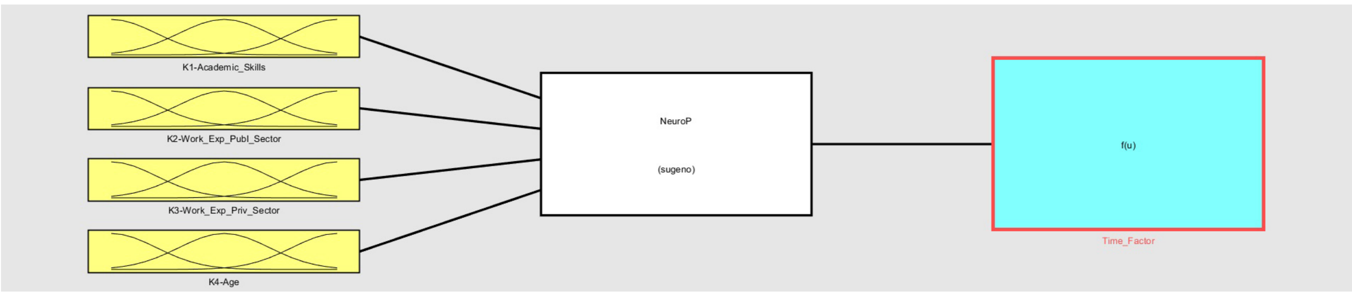

Figure 5. Overview of the fuzzy system model.

In Figure 6, academic skills have a more dominant effect on the time-factor. Best results for the time-factor were achieved for employees with maximum values of academic skills and experience in the public sector.

Figure 7 demonstrates the significance of experience in the private sector as opposed to academic skills. The curve shows a steeper tendency as work experience progresses.

Age contributed less to the time-factor compared to academic skills. This proves that there is no efficiency increase as much as academic skills contribute to this purpose. This is further shown in Figure 8.

Comparing those two factors (Figure 9), there was an interesting finding of employees who have previous experience in the private sector tending to perform better in all cases reported.

The slope of the surface in Figure 10 indicates the solid impact of work experience in the public sector as opposed to age.

Figure 11 demonstrates the solid impact of experience in the private sector as opposed to the age of employees. Small fluctuations towards high values of K3 were interpreted due to missing relevant data records in this area.

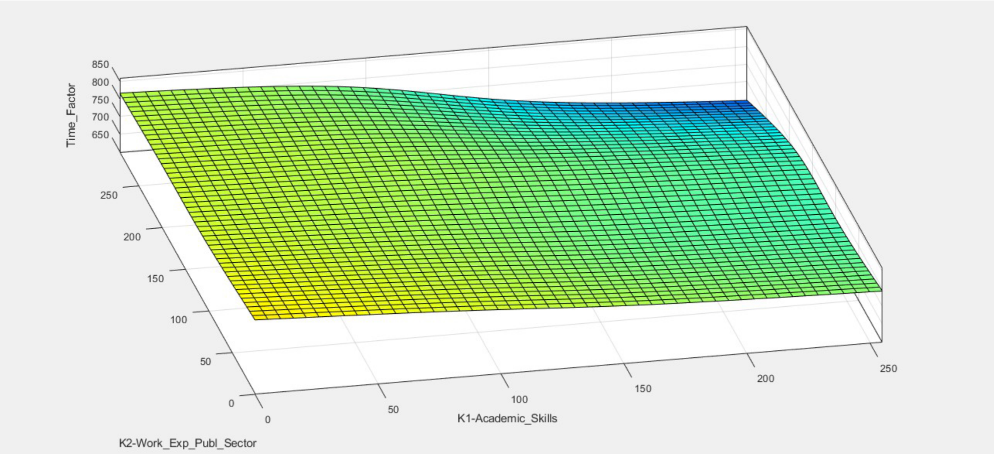

Figure 6. Results of academic skills—work experience in public sector.

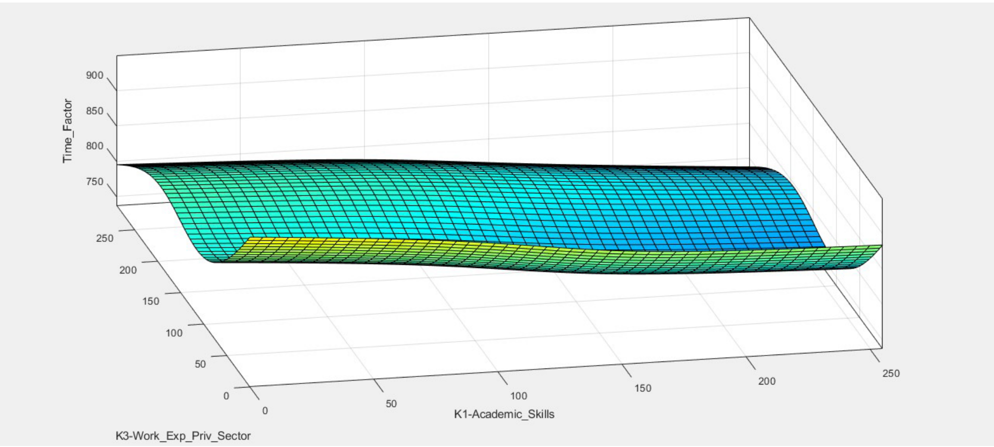

Figure 7. Results of academic skills—work experience in private sector.

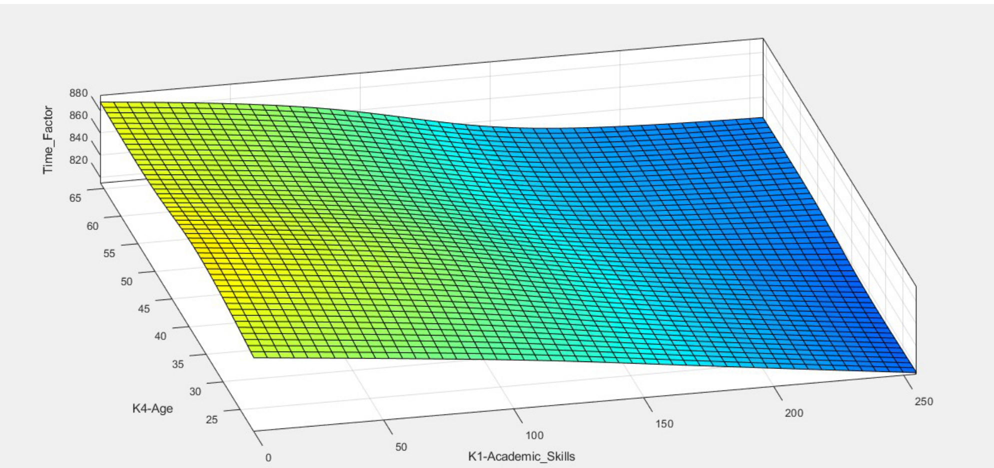

Figure 8. Results of academic skills and age factors.

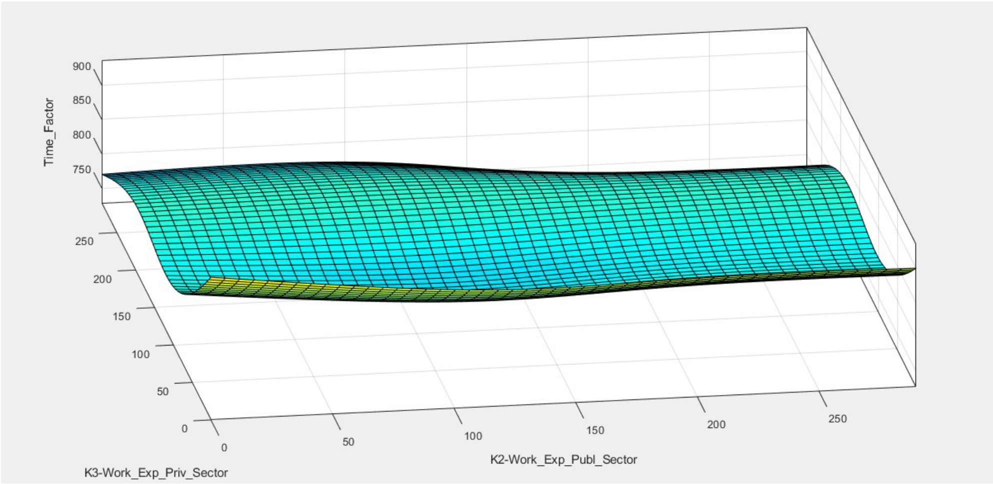

Figure 9. Results of work experience in public and private sector.

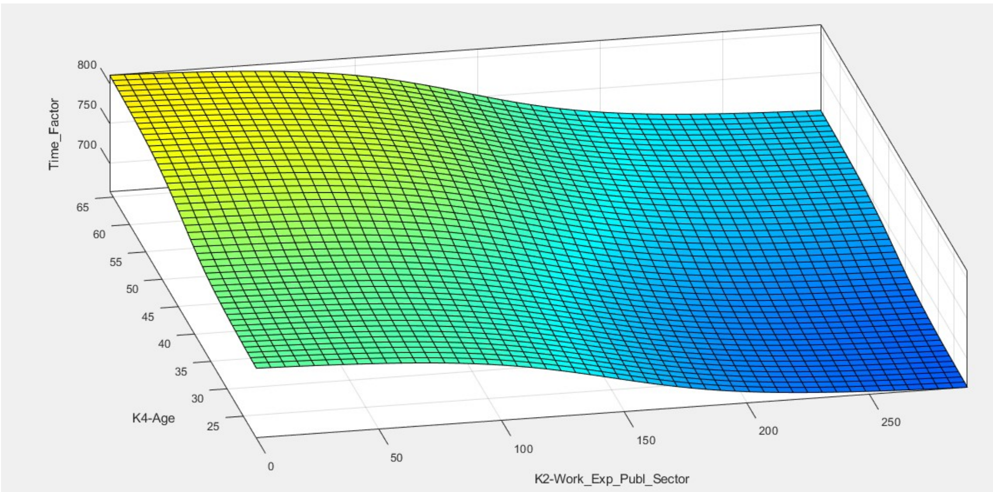

Figure 10. Results of work experience in public sector and age.

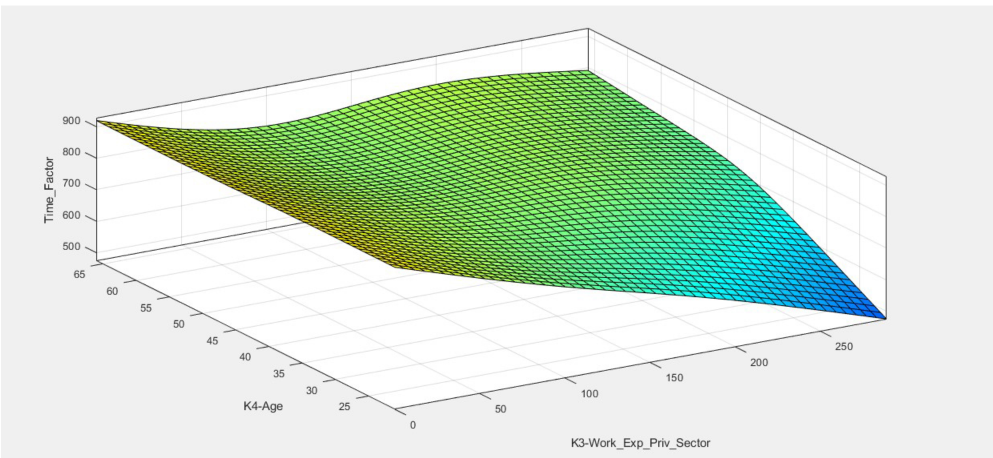

Figure 11. Results of work experience in private sector and age.

Two-hundred records of employees were deployed as the training set, while ninety-five were used for the verification of the system as the testing data. The time frame for the data samples was limited to two years. Almost 9% of the initial data were inaccurate due to never-ending or unassigned tasks, thus providing a time-factor with invalid ranges (infinite values). The RMSE was limited to 10.3 on fifty epochs, one-hundred and four parameters, and sixteen fuzzy rules as seen in Figure 12, thus providing an acceptable time-factor since the output was an elaboration of human productivity statistics and not strict machine time fractions. The model performed as expected for the testing data, avoiding abnormal fluctuations, thus proving immunity to overfitting effects. Therefore, it is remarkable to show that academic skills caused more impact compared to the experience in the public sector on the productivity of the employees, while previous experience in the private sector could be regarded as the key point of the research. On the other hand, age was considered more like a neutral factor in the equation. It has to be highlighted that the graphs provide the tendency to show the indicative impact of the corresponding skill.

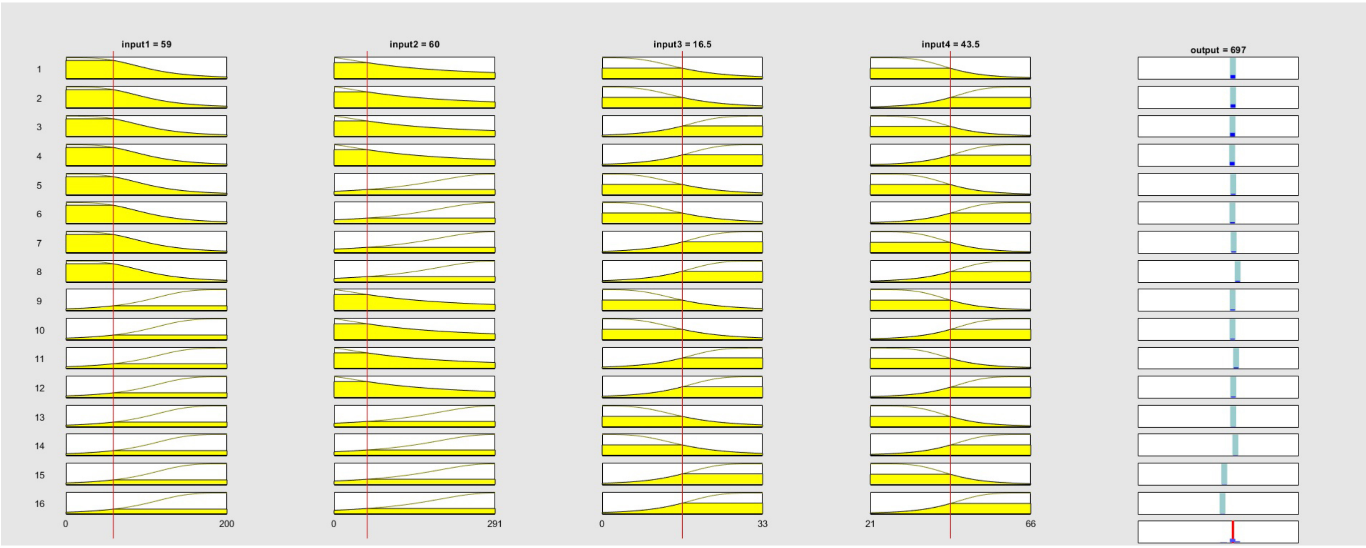

Figure 12. Rule viewer of the the fuzzy inference system.

The validation of the proposed approach was performed by deploying the corresponding ANFIS functionality ("evalfis") on the testing records of the employee list. Figure 13 provides valuable information for the accuracy and validity of the process. As seen in Figure 14, the real data, as perceived from the system itself, were compared to the predicted results of the Matlab simulation. Our assumption was a low RMSE (10.3), as indicated during the training procedure.

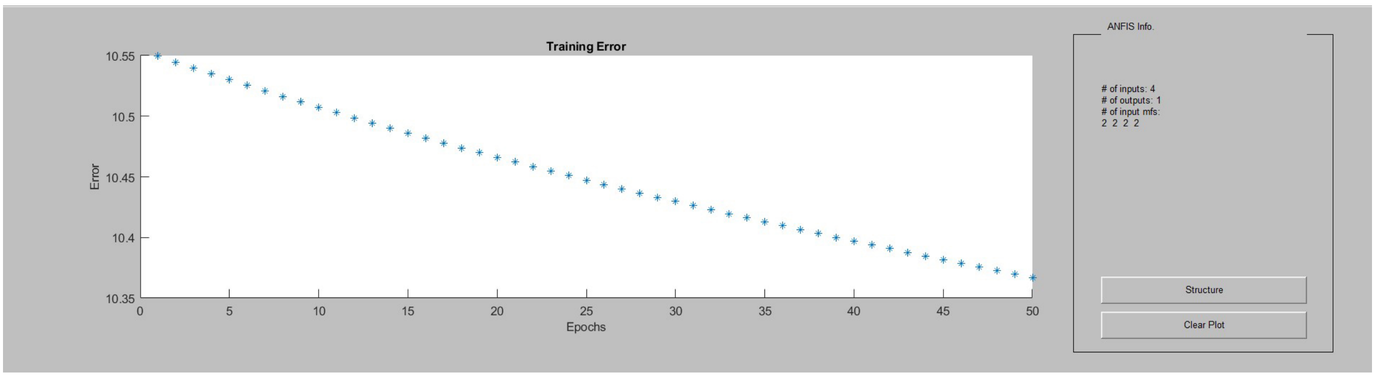

Figure 13. Training error.

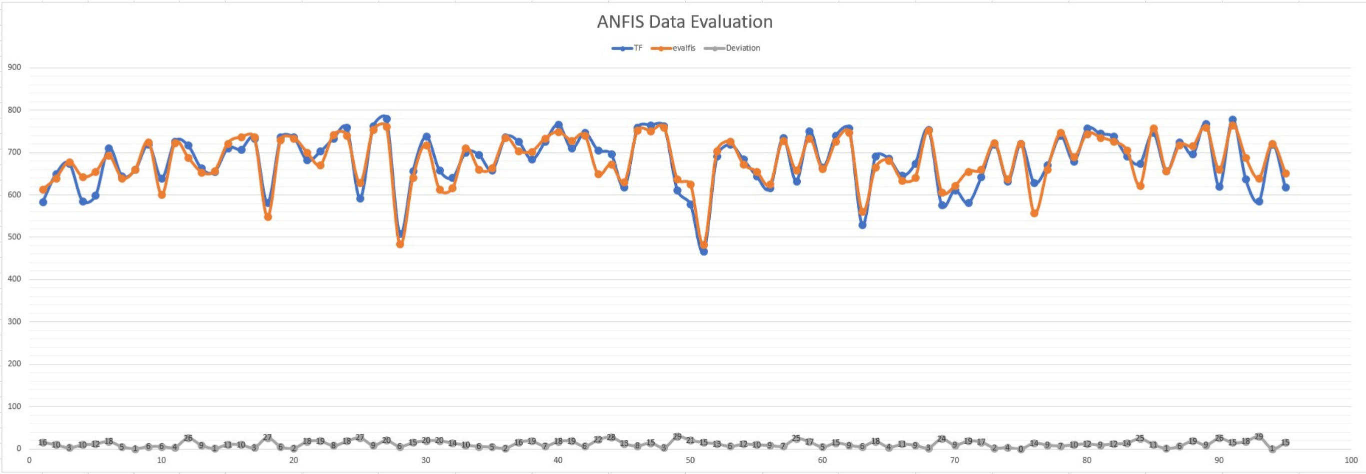

Figure 14. ANFIS validation.

It should be highlighted that outliers were taken into consideration, such as the pre-filtering of the infinite time-factor being automatically discarded according to the discussion above. All four inputs K1 up to K4 were quantified from the official data records of the HR department, so no out-of-bounds value could potentially occur. A potential increase in the inputs would increase the complexity in terms of the epoch evaluation. The system efficiency upon deployment in a real-time system would depend on the hardware itself, but is subject to further investigation.

5. Discussion

5.1. Time Complexity of ANFIS

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a computational model that is often used to model complex nonlinear relationships between inputs and outputs. The time complexity of ANFIS can vary greatly based on a variety of factors, such as the size of the dataset, the number of inputs and outputs, the complexity of the fuzzy rules, and the optimisation algorithm employed.

In general, ANFIS is considered to possess a high time complexity as a result of its iterative optimisation procedures, such as gradient descent or the Levenberg–Marquardt algorithm, which are used to minimise the error between the actual and predicted outputs. In terms of computational cost, the forward pass, or prediction step, of ANFIS can be characterised by a time complexity of $\mathcal{O}(M \times L)$, where M is the number of fuzzy rules and L is the number of inputs. The time complexity of the backpropagation step, or training step, is more complex and dependent on the optimisation algorithm utilised, but can typically be described as $\mathcal{O}(n)$, where n is the number of iterations required for convergence.

Despite its computational cost, ANFIS continues to be utilised in a range of applications due to its ability to effectively learn and represent complex nonlinear relationships. The use of ANFIS in the academic and research communities is prevalent, and its study continues to be an area of active investigation in the field of machine learning and artificial intelligence.

5.2. Limitations

The limitations of the study can be considered in terms of both the data sample and the methodology used. In terms of the data sample, the results may not be generalizable to other populations or contexts, as the sample size was limited and may not be representative of the entire population. To address this limitation, future studies could consider collecting data from a larger and more diverse sample.

Additionally, the study used ANFIS as the methodology for modelling the employee assessment and ranking system in the public sector. While ANFIS provides a valuable tool for this purpose, it may have limitations in terms of its accuracy, particularly when the data sample is limited or the input variables are not fully specified. To address this limitation, future studies could consider incorporating additional variables into the model or using more advanced modelling techniques.

In terms of the limitations of ANFIS in the public sector, the implementation of ANFIS may require specialised knowledge and computing resources, which could limit its use in certain organisations. Additionally, data privacy and security concerns may arise when using ANFIS in the public sector, as sensitive information may be collected and processed. To address these limitations, future studies could consider incorporating data protection measures into the design of the ANFIS model or exploring alternative modelling techniques that address these concerns.

In summary, the limitations of the study highlighted areas for improvement and further investigation in future studies. By addressing these limitations, future research can build upon the findings of this study and provide a more comprehensive understanding of the factors that shape the productivity profile of employees in the public sector. Additionally, further research can help to address the limitations of ANFIS in the public sector, making it a more viable tool for decision-making, policy analysis, and resource allocation in the public sector.

5.3. Computing Cost and Economic Effectiveness

In the current study, the computing cost and economic effectiveness of ANFIS were not evaluated. However, this is an important aspect to consider when implementing ANFIS in real-world applications. ANFIS models can be computationally intensive, particularly for large and complex datasets. This may result in high computing costs and may limit the feasibility of using ANFIS in certain organisations, particularly those with limited computing resources. Additionally, the cost effectiveness of ANFIS should also be considered in terms of the benefits it provides in terms of decision-making, policy analysis, and resource allocation. While ANFIS can provide valuable insights and improve the accuracy of predictions, its implementation may require significant time and resources, which could impact its overall economic effectiveness. Therefore, it is important to carefully evaluate the computing cost and economic effectiveness of ANFIS when considering its implementation in real-world applications. This may involve conducting cost–benefit analyses, comparing ANFIS to alternative modelling techniques, and considering the trade-offs between the computational requirements and the benefits provided by ANFIS. In conclusion, ANFIS has the potential to provide valuable insights for decision-making in the public sector, but its implementation requires careful consideration of the computing costs and economic effectiveness. Factors such as the size and complexity of the data, the available computing resources, and the specific requirements of the application should be taken into account when evaluating the feasibility of using ANFIS. Future research could focus on developing strategies to reduce the computational requirements of ANFIS and on comparing the performance and cost effectiveness of ANFIS with other modelling techniques. Furthermore, the limitations of ANFIS should be carefully considered and addressed in future studies to improve its accuracy and usefulness in real-world applications.

Ultimately, the implementation of ANFIS in the public sector will require a comprehensive and interdisciplinary approach, involving experts from various fields, including computer science, operations research, and public administration. By considering the technical and economic feasibility of ANFIS and by addressing its limitations through further research, the public sector can harness the potential of this powerful tool to support effective decision-making, policy analysis, and resource allocation.

6. Conclusions and Future Work

The analysis from current research provided valuable information on the critical factors that shape the productivity profile of each employee in the public sector. The proposed model extends the conventional theoretical framework of employee assessment and ranking, providing emphasis on the public sector. The results indicated the significant impact of work experience in the private sector compared to the public sector, and academic skills, reinforcing the opinion that age does not affect the total outcome at a significant level. The data sample was adequate to provide valuable information, but more records could be added to future research with more membership functions for ANFIS modelling. The main advantage remains the fact that the capacity factor for each employee is extracted and calculated directly from the system without taking into consideration the subjective proposals of execution times from experts. In addition, the proposed model can be deployed as a distributed system that supports decision-making processes. In case more inputs are needed, they can be incorporated into the existing modelling. Employees' performance is based only on task deliveries and job completions in such a way that the system can be treated as self-learning. It has to be noted that the availability of open data on public bodies can further enhance the prediction of the capacity factor with more accuracy.

The model evaluates corporate aspects and advice in accordance with the objectives of the organisation. It may not only cut expenses during the phase of selection, but also minimise conflict and hidden costs during the phase of implementation. On the other hand, the limitations of the current model include primarily a shortage of the sampling range due to limited employee records. In order to have a more precise time-factor forecasting, three MFs per input would provide more accurate results, thus making the surface analysis smoother. Additional factors should be taken into consideration such as language skills, as well as soft-skill-related factors such as communication and risk management abilities. Approaches that are related to the working environment and could be quantified with IoT platforms such as weather condition measurements could modify the results even more. Nevertheless, a migration of the proposed model to an HW platform with real-time statistics is fully dependent on the HW specification and is a case study for future development.

The next step is to formalise the findings and proceed with the evaluation and definition of the tasks that each employee can perform based on the values of the capacity factor. The deployment of an ad hoc mechanism that calculates the capacity of each node and redistributes the assigned jobs could form a new approach to HR services having as a primary goal the perseverance of flow and load regulation in every department in the public sector.

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