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APPLICATION OF NEURO-FUZZY SYSTEM FOR PREDICTING THE SUCCESS OF A COMPANY IN PUBLIC PROCUREMENT

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Abstract: *The paper presents a neuro-fuzzy system for evaluating and predicting the success of a construction company in public tenders. This model enables companies to operate sustainably by assessing their own position in the market. The model was based on data from a seven-year study, where data from the first six years were used to adjust the model, while data from the last year of the study were used for testing and validation. The neuro-fuzzy model was tuned using the Artificial Bee Colony algorithm*

Key words: *Fuzzy Sets, Neuro-fuzzy system, Artificial Bee Colony.*

1. Introduction

The companies operating in the market in any area (marketing, information technology, manufacturing, consulting services, etc) are constantly facing with the problems of existence and continuous maintenance of the level of services, on one hand, as well as with the problem of evaluating competition, on the other hand (Pamucar & Bozanic, 2018). Knowing of the competition is the first step towards winning on the market (Rietveld & Schilling, 2020).

When considering evaluation of competition and predicting results of consulting services in construction, it should be borne in mind that predicting of performance in public tenders is a key mission of a consulting company in order to neutralize negative impact of competition. Therefore, in order to quickly adapt to market demands, it is necessary to analyze conditions and changes in the environment, as

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well as to measure changes within the entire investment area. This implies evaluation of the economy stability in the subject area, as well as knowledge of technological innovations. Something new needs to be offered, and the technical innovations that companies are developing help (Del Giudice et al., 2019).

One of the most important questions for sustainable management of consulting companies is how to predict whether the consulting company will win in public bidding with other consulting companies. This implies that it is necessary to evaluate the competition and predict the results of consulting services in the construction industry for a particular company, respectively, the possibility of being awarded a job on a tender realized as public procurement. In order to win a tender in public procurement, company's bid must be more favorable than other bids (Hanák et al., 2021). As a logic consequence, there is the need of analyzing and evaluating the parameters that influence such success over a certain period of time (several years of company's previous business operations), with the tendency to provide a prediction for the following period based on the results obtained by such analysis.

In the business system of every company, especially consultants in the field of construction industry and investment, there are uncertainty, subjectivity and imprecision. In certain situations also, decisions are made on the basis of experience, intuition and subjective assessment of some parameters. Uncertainty and complexity are caused by the specifics that construction as a business area has, compared to other areas. Specificities are a consequence of complex nature of investment activities, external organizational and economic factors and the conditions under which construction production is taking place. Complex nature of investment activities initiates a large number of activities and long-term realization. Therefore, the selection of investment is very difficult and requires considering many aspects (Puška et al., 2018). Therefore, in formulating methodological principles for predicting the success of consulting companies in construction, it is necessary to use mathematical methods which in a satisfactory way treat uncertainty, subjectivity, and imprecision (indeterminacy). Thus, the methods based on neuro-fuzzy modeling and generating of rules from data imposed themselves as the most suitable mathematical apparatus.

Accordingly, the subject of this paper is the selection of parameters that influence winning of consulting jobs in public tenders and formation of adequate strategic decision-support system that enables managers to make quality and sustainable decisions. In this regard, the aim of the research is to create a decision-support model that allows predicting the performance of the observed company in public tenders, respectively, the rank prediction of the company, compared to the competition. Consequently, the objective is to find out and conclude which jobs have the best prognosis, which enables undertaking of concrete strategic measures in the long-term policy of a specific consulting company. In order to achieve this goal, research and monitoring of the results of a consulting company during seven-year period (2010 - 2016) is performed. On the basis of these data, a prediction model is made and its validation is carried out.

The prediction model presented in this paper belongs to the group of multi-criteria decision-support systems and it is designed using the Neuro-Fuzzy technique (NF) and the Artificial Bee Colony (ABC) algorithm – the NF-ABC model. Based on seven-year research, three variables are identified that affect the rank prediction of the consulting companies in public tenders. Using fuzzy technique, initial Fuzzy Logic System (FLS) is modeled and initial rule base is created. In the following phase of the neuro-fuzzy modeling, the FLS is mapped into a five-layer adaptive neural network and the training of the neuro-fuzzy model is carried out using the ABC algorithm.

Before the training of the NF-ABC model, the validation of the data collected during the research is performed using the $\chi 2$ test.

The rest of the paper is organized as follows. In the second part of the paper, the analysis of the literature is performed and the overview of the techniques used to rank the bidders in public procurements is provided. In the third and the fourth part of the paper, the architecture of the neuro-fuzzy model and the training procedure using the ABC algorithm are presented. In the fifth section of the work, the validation of the model is carried out and the managerial applications of the NF-ABC model are shown. In the sixth section of the paper, the concluding observations with directions for future research and model improvement are provided.

2. Literature revew

The success of business in the construction industry has been the topic dealt by numerous authors, pointing out the importance and the possibility of applying different techniques and methods to solve numerous issues depending on the type of company/business. Some papers (Maybeck, 1979; Singh, 1980; Mockler, 1972) point to essential business terms and some specifics in the construction industry. Although these papers were published in the second half of the 20th century, findings obtained in them are still relevant in analyzing the impact of changes, distortions in business environment and the importance of choosing business alternatives.

The problem of bidder selection in public procurements in various areas conditioned a large number of research procedures that resulted in numerous scientific papers within the previous decades. This problem is present both in procurements implemented in the construction sector, as well as public procurement procedures in the public sector, with almost identical objectives related to the corresponding product quality, timely delivery, the best price, etc (Zak, 2015; Falagario et al., 2012). The selection of bidders in public procurement procedures is multi-criteria problem, and the application of multi-criteria optimization model is convenient tool for decision making. When implementing this procedure, it is necessary to define first the model that will be applied, and then the criteria in relation to which the selection will be made. The study of the selection of criteria used in procurement procedures began in the 70s of the twentieth century with the papers of a number of authors, among which Dickson (1966) stands out. Later, similar research procedures were carried out (Moore & Fearon, 1973; De Boer et al., 2001; Kahraman et al., 2003; Dobi et al., 2020; Chai et al., 2013) showing that the criteria such as price, quality, timely delivery, technical capacity of suppliers are most often set as conditions for contract award.

Chai et al. (2013) carried out the categorization of the literature which deals with the issue of selection of service providers in public tenders considering 123 scientific papers. These papers systematically present a review of the literature regarding the application of multi-criteria models in the period from 2008 to 2014. The research included was divided into seven categories, in which 26 techniques of multi-criteria decision making were applied which were grouped into three sections: (1) Multi-Criteria Decision Making (MCDM) techniques, (2) Mathematical Programming (MP) techniques, and (3) Artificial Intelligence (AI) techniques. The following table (Table 1) presents an overview of the models used in the last ten years to define ranks of bidders in public procurement.

Table 1. Overview of literature and models for defining ranks of bidders in public procurement

Literature	DM techniques
Amid et al. (2011)	Weighted max–min fuzzy AHP
Amin and Zhang (2012)	Multiobjective mixed integer LP
Buyukozkan and Cifci (2012)	ANP, TOPSIS, DEMATEL
Božanić et al. (2021a)	Neuro-fuzzy system
Bhattacharya et al. (2010)	AHP with Cost factor measure; QFD technique
Rodríguez et al. (2020)	Random Forest Classifier; Bidders Recommender Algorithm
Chan and Chan (2010)	AHP model for apparel industry
Chua et al. (2015)	AHP
Crispim and De Sousa (2010)	Fuzzy TOPSIS; regarding virtual enterprises
Dotoli et al. (2020)	AHP, PROMETHEE, DEA, MAUT
Feng et al. (2011)	Collaborative utility; Tabu search based algorithm
Ferreira and Borenstein (2012)	Fuzzy Bayesian model; Influence diagrams
Karamașa et al. (2021)	Entropy, MAUT
Ho et al. (2011)	ANP; QFD technique
Hosseini and Barker (2016)	Bayesian network model
Ishizaka et al. (2012)	AHP-based sorting approach
Kuo et al. (2015)	Fuzzy ANP and fuzzy TOPSIS
Labib (2011)	Fuzzy AHP linguistic expression; Fuzzy logic
Levary (2008)	AHP
Liu and Zhang (2011)	Combine entropy weight and ELECTRE-III
Mafakheri et al. (2011)	AHPin Two-stage dynamic programming
Razmi et al. (2009)	Mixed integer NLP
Rezaei and Davoodi (2012)	Multiobjective mixed integer NLP
Rezaei et al. (2016)	BWM method
Sen et al. (2010)	Max–min method
Vahdani and Zandieh (2010)	Extend ELECTRE for interval values
Yu et al. (2012)	AHP, MOP
Zhang and Liao (2022)	A stochastic cross-efficiency DEA
Zhao and Guo (2014)	Fuzzy TOPSIS

De Boer et al. (2001) defined four stages of solving the problem of bidder selection including problem formulation, formulation of criteria, qualification and final selection. They stated that most authors paid the greatest attention to final selection, which was significant for further prediction of a company's activities. From the literature dealing with the issue of bidders' rank in procurement procedures in the last decade, it can be concluded that the AHP method was particularly used. Dobi et al. (2010) made a comparison of the AHP and the ANP when making decisions in selecting the most favorable bidder in the procurement procedures and evaluating the criteria. Similarly, Sameh et al. (2016) are used for pair wise comparison and prioritization of criteria; classical AHP and fuzzy AHP. Some authors, such as Adil et al. (2014), also use hybrid models that combine multiple multi-criteria models – the

TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution) and the COPRAS (COmplex PRoportional Assessment) when selecting bidders for the needs of Maldivian Public Sector. Bana e Costa et al. (2007) propose bidder evaluation model using the MACBETH (Measurement Attractiveness by a Categorical Based Evaluation Technique) method by which the weights of criteria are not directly evaluated based on relative importance of criteria, but the range of criteria values of variants is considered.

According to the author's knowledge, there are rare cases of application of other models for bidder ranking in public bidding, which do not fall under the scope of multi-criteria techniques. Ltifi et al. (2016) indicate that data research has great potential in extracting useful knowledge from a large amount of data for dynamic decision making. Thus, Ltifi et al. (2016) propose using neuro-fuzzy techniques to create dynamic models that have the ability to adapt to changes in the environment. Son and Kim (2015) demonstrated the possibility of applying data mining techniques for predicting costs and project scheduling based on the level of definition of certain components. They propose a three-step procedure for achieving this objective: previous processing, selection of variables and development of a prediction model.

The rapidly growing and large amount of data in the field of construction, together with the necessity for data analysis, created urgent need for powerful tools that could generate knowledge and predictions from large data sets. Traditional and hybrid multi-criteria models cannot adequately respond to such requirements (Zhun et al., 2016). Zhun et al. (2016) point out the importance of using data mining techniques, both for describing and predicting activities, in various business areas. By analyzing the literature dealing with models for predicting the performance of companies in public procurements, it is noticed that there are no models for predicting the performance of construction companies in public procurements. There is a lack of application of fuzzy logic, adaptive neuro-fuzzy models, linear and dynamic programming, as well as heuristic and meta heuristic models. As previously shown (Table 1), most papers discuss the rank of bidders in public procurements using classic multi-criteria decision-making methods. That is why the development of the NF-ABC model for the prediction of bidders' ranks using adaptive neuro-fuzzy techniques and the ABC algorithm is a logical step towards overcoming of this gap.

3. Neuro-fuzzy model for predicting results of consulting services in construction

The NF-ABC model for predicting the rank of consulting companies in public tenders uses the benefits of fuzzy sets and fuzzy logic systems, combined with the concept of artificial neural networks. Fuzzy logic provides mathematical description of uncertainties that occur in human cognitive processes, such as thinking and reasoning (Ghazinoory et al., 2010; Božanić et al., 2015; Pamučar et al., 2016a; Pająk, 2020; Jokić et al., 2021). Thus, using fuzzy logic and approximate reasoning algorithm it is enabled concluding based on incomplete and insufficiently precise information (Pamučar et al., 2016b; Pamučar et al., 2016c; Gharib, 2020; Božanić et al., 2021b; Tešić et al., 2022). On the other hand, artificial neural networks possess architecture built on the concept of artificial neurons imitating biological nerve systems in its functioning. One of the most important processes that enable artificial neural networks is example-based learning. Combining fuzzy logic concepts, which provide a mechanism for concluding with incomplete and insufficiently precise information, and artificial neural networks which provide learning, adaptation, and generalization possibilities, very powerful hybrid neuro-fuzzy systems are obtained that find its application in solving many real engineering problems.

From the above mentioned can be concluded that both concepts have advantages/disadvantages: (1) Neural networks can learn from examples - automatically, but it is difficult to describe the knowledge acquired in this way and (2) Fuzzy logic allows approximate conclusion, but it does not have the property of auto adjusting (adaptability) (Božanić et al., 2014). Basic idea of neuro-fuzzy adaptive technique is founded on fuzzy modeling and learning methods based on the given data set. Due to these advantages, in this paper the authors have chosen to develop models for predicting the success of consulting companies in public tenders in construction based on adaptive neuro-fuzzy techniques.

As stated in the previous section, three criteria are identified on the basis of which the prediction of the potential rank of a consultant service provider is carried out:

Input 1: Institution (X_1∈[1,4]). This input variable describes the nature of the investor which announces the tender for public procurement of services: state institution/company, public institution/company, municipality, private legal entity and natural person.

Input 2: Work type (X_2∈[1,16]). Input variable work type refers to a type of consulting services a consultant can perform. This model covers the following consulting services in the construction industry: geodetic recording, testing, assessment act elaboration, elaborate creation, elaboration of project management plan, project elaboration, regulatory plan elaboration, strategy development, study development, measuring, monitoring, designing, spatial planning, auditing and nostrification of technical documentation, expert supervision and technical inspection.

Input 3: Number of participants in public procurement (X_3∈[1,7]). Input variable number of participants in public procurement refers to the expected number of bidders of consulting services in public procurement.

From the neuro-fuzzy model it is obtained the Output: Rank of the consultant service provider (Y ∈[1,7]), respectively, the ranking of the bidders is performed depending on the input parameters. In addition to the mentioned variables (Input 1 - Input 3 and Output), the neuro-fuzzy model also had the attribute of financial value of the bid that was not directly considered due to the following restrictions: (1) because of business secrets and 2) based on the available data about the tenders in the period of observation, it is noted that for the investors, the price of the service was the most important when choosing the best bidder. Since the prices of services for each individual tender are presented and analyzed through ranks, it can be concluded that this attribute is indirectly included in consideration through the output variable, respectively, the rank of the bid.

Using descriptive statistics method, non-parametric statistical tests ($\chi 2$ test) and generating rules from data in the analytical monitoring process, the design of the NF-ABC model for predicting the rank of consulting companies in public tenders is carried out. Descriptive statistics is used to evaluate the validity of the collected data. The $\chi 2$ test is used for: (1) checking statistical significance between observed and theoretical frequencies; (2) checking the membership of independent data sets, expressed as frequencies on the same data population; (3) determining whether there is a significant difference between the groups of data obtained on one sample; (4) determining whether there is a connection between data sets and (5) calculating the degree of connection between the data sets in the form of correlation coefficient.

The intervals of the input parameters of the neuro-fuzzy model were determined based on the parameters from the database obtained by the research in seven-year period from 2010 to 2016. During the research, the data were collected and a database was created with the results achieved by particular consulting company during the observed seven-year period. The acquired database was later used to train neuro-fuzzy model to predict the results of consulting services. One part of the data obtained (from 2010 to 2015) was used to train neuro-fuzzy model, while the data from 2016 were used to test and validate the model.

In the initial phase of the neuro-fuzzy model design, a set of linguistic rules, types and parameters of membership functions (MF) describing input/output variables of the model are defined. In the neuro-fuzzy model, the Gaussian MFs were used to describe the three input variables. Gaussian MFs are chosen because: (1) they describe well the input variables, (2) they ensure satisfactory sensitivity of the model, (3) with their adjustment it is provided the smallest output error, and (4) they are easy to manipulate when setting the model. Since it is a zero-order Sugeno fuzzy logic system (FLS) mapped to neural network, the output variable Range of the consultant service provider (*Y*) is presented by 15 MFs presented by constants ($Y = ax + by + c$, $a = b = 0$). The output variable Y is scaled within the interval [1, 7]. By comparing the output parameters of the FLS and the desired set of solutions, it was noted that the difference between the expected rank from the database and the output values from the FLS was not within the limits of tolerance. Changes to the type and parameters of the MF, as well as changes to the rules in the base of the FLS did not contribute to the approximation of the output values to the values from the training base. In the next step, the FLS was mapped to a five-layer neuro-fuzzy model (Figure 1), with the goal of further adjusting and obtaining output data that are closer to the data from the training set.

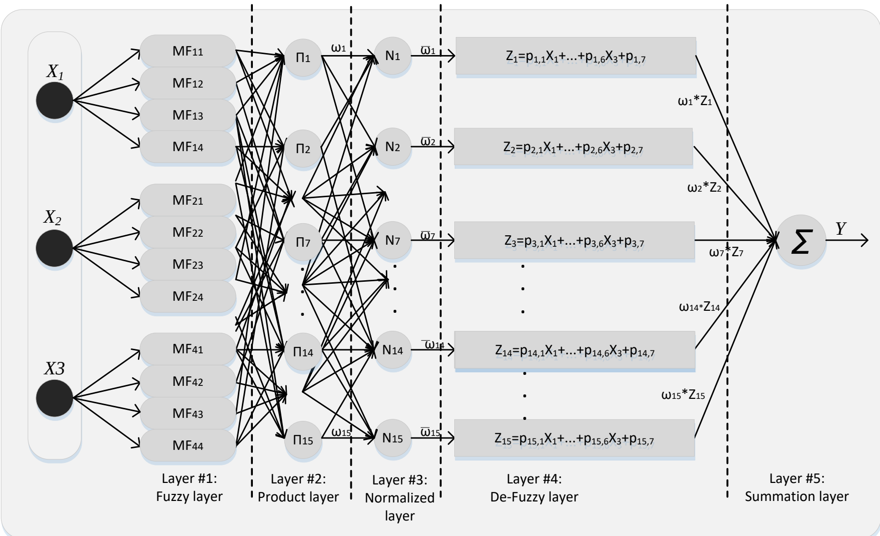

Figure 1. Neuro-fuzzy model for determining the CR value of the network branches

The input layer consists of three units: X_1, X_2 and X_3. It simply transfers inputs further via the interconnections to the hidden or first layer. The all units in the input layer (X_1, X_2, X_3) are connected with the four units in the first layer. The strengths of connections between the units in the input layer and the units in the first layer are crisp numbers equal to 1.

The first layer consists of 3+4 units representing the number of verbal descriptions quantified by fuzzy sets ("very low", "low", "medium", "high") for each input variable (X_1, X_2, X_3). Every unit in the first layer is an adaptive unit with an output being the membership value of the premise part. The number of units in the second layer equals the number of fuzzy rules. Every unit in this layer is a fixed unit that calculates the minimum value of incoming two inputs. The outputs from this layer are firing strengths of rules. For example, the output from the first unit in the second layer is:

$$\omega_1 = \min\left\{\mu_L(x_1), \mu_H(x_2), \mu_M(x_3)\right\} \tag{1}$$

The third layer has 15 adaptive nodes that calculate sections of the fuzzy sets (consequent) with the maximum of the incoming rules' firing strengths. The normalization of the weight coefficient of every neuro-fuzzy model rule, $\overline{\omega}_k$,is calculated using the expression for additive normalization

$$\overline{\omega}_k = \frac{\omega_k}{\sum_{i=1}^{15}\omega_i} \tag{2}$$

where k ($k = 1,...,15$) presents the number of rules in the neuro-fuzzy model.

The single unit in the fourth layer is a fixed unit that computes the overall output of the neuro-fuzzy model:

$$\mu_M\left(Y\right) = \max\left\{\mu_{V1}\left(Y\right),...,\mu_{V15}\left(Y\right),\right\} \tag{3}$$

The obtained output is then defuzzified in the single unit in the fifth layer. The selection of the final crisp value can be made in various ways. In this paper calculates the action that is closest to the center of gravity (Center-of-Gravity method):

$$O = Overalloutput = \sum_{k=1}^{15}\overline{\omega}_k Y_k = \frac{\sum_{k=1}^{15}\omega_k Y_k}{\sum_{k=1}^{15}\omega_k} \tag{4}$$

The neuro-fuzzy model parameters were adjusted using the Artificial Bee Colony (ABC) algorithm (Pamučar et al., 2016d). The ABC algorithm showed significantly better results during training when compared to standard algorithms (back propagation and hybrid algorithms) that were implemented in the toolbox of the Matlab R2008a. The training of the ANFIS with back propagation and hybrid algorithm was done under the same conditions that were valid when applying the ABC algorithm. The training with back propagation and hybrid algorithms lasted longer than with the ABC algorithm, and the error at the end of the training was 2.891 (back propagation algorithm) and 3.542 (hybrid algorithm), compared to the error of 0.13 in the training with the ABC algorithm (Figure 2).

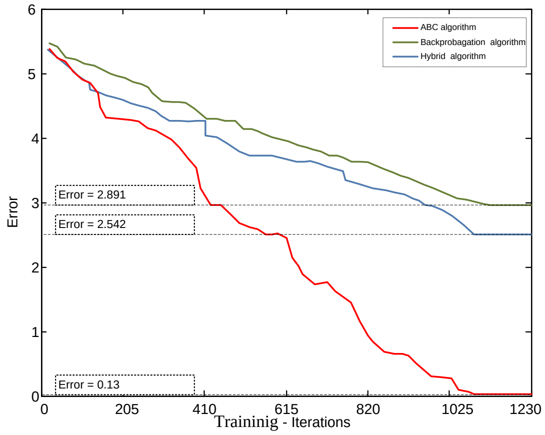

Figure 2. ABC, backpropagation i hybrid algoritam - traininig error

The attempt to increase the number of training epochs (from 60 to 1500) and to change the type of MF in order to additionally reduce the error using back propagation and hybrid algorithm did not lead to any significant improvement in the results. The error remained at the level of the previous testing. This confirmed the author's determination for applying the ABC algorithm. In the Figure 3 are graphically presented the results of comparing the training data set with the output parameters of the neuro-fuzzy model after the training with the ABC algorithm.

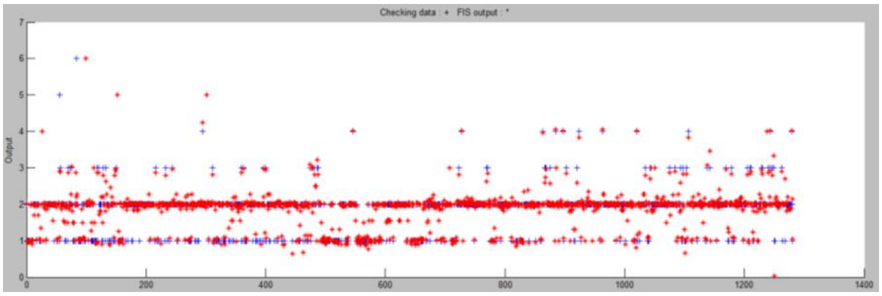

Figure 3. Comparison of the training data set with the results of the NF-ABC model

Based on the Figure 3, it can be concluded that the projected neuro-fuzzy model provides satisfactory prediction of the bidders' ranks with the negligible error of 0.13. Since it is a decision-support system for rank prediction, the error value of 0.13 is negligible and it can be concluded that the neuro-fuzzy model is successfully set.

4. Testing and validation of the neuro-fuzzy model

The model presented was tested in a total of 239 public procurements in which the consulting company investigated took part in 2016. In the Table 2 is presented a part of the data collected during 2016 that were used for testing and validation of the NF-ABC model. Due to the limited space for presenting the results and the fact that it is a large number of data (a total of 239), in the following table is shown only the part of the data used for model validation.

Table 2. Data collected during 2016 used for neuro-fuzzy model testing

Nu-mber	Institution	Work type	Partici-pants No.	Rank
	Public	Measurements	4	3
	Private legal entity	Monitoring	3	1
	Public institution/company	Project creation	5	2
	Municipality	Regulation plan creation	5	2
	Municipality	Measurements	4	2
	State institution/company	Project creation	5	2
	Public institution/company	Project creation	5	2
	Municipality	Elaborate creation	4	2
	Private legal entity	Testing	6	3
	Public institution/company	Expert supervision	5	1
	Municipality	Regulation plan creation	4	2
	Public institution/company	Project creation	6	2
	Public institution/company	Revision and nostrification	4	2
	State institution/company	Project creation	5	2
	State institution/company	Project creation	5	2
	State institution/company	Project creation	5	2
	State institution/company	Project creation	5	2
	Municipality	Management plan creation	4	2
	Municipality	Regulation plan creation	3	2
	State institution/company	Project creation	5	2
	Municipality	Management plan creation	4	2
	Public institution/company	Project creation	6	2

Nu-mber	Institution	Work type	Partici-pants No.	Rank
...	...	...	...	...
	State institution/company	Expert supervision	4	1
	Municipality	Testing	4	3
	Public institution/company	Expert supervision	4	2
	Public institution/company	Expert supervision	5	1
...	...	...	...	...
	Municipality	Spatial planning	5	1
	State institution/company	Project creation	6	3
	Public institution/company	Revision and nostrification	5	2
	Public institution/company	Expert supervision	7	1
	State institution/company	Project creation	5	2
	Municipality	Project creation	4	2
	Municipality	Expert supervision	6	4
	Public institution/company	Monitoring	4	3
	State institution/company	Expert supervision	6	1
	Public institution/company	Geodetic recording	5	1
...	...	...	...	...
	Public institution/company	Assessment act creation	4	3
	State institution/company	Project creation	5	3
	Municipality	Project creation	5	2
	Municipality	Revision and nostrification	4	2
	Municipality	Spatial planning	5	1
	Municipality	Regulation plan creation	7	1
	Municipality	Expert supervision	5	2

By putting input parameters (Table 2) through the NF-ABC model, the results are obtained which are shown in the Table 3. A comparative overview of the results collected for 2016 and the rank prediction given by the NF-ABC model are shown in the Table 3. In order to have an overview of the quality of the results, in the Table 3 the target ranges are also shown next to the outputs of the NF-ABC model.

Table 3. Comparative overview of the results of the neuro-fuzzy model and the control data group

Target	ANFIS	Target	ANFIS	Target	ANFIS	Target	ANFIS	Target	ANFIS
3	2.85	3	2.77	3	3.09	2	1.99	3	3.00
3	3.00	2	1.82	1	1.00	2	2.00	4	3.98
2	2.00	1	1.04	2	2.00	2	2.00	2	2.00
2	2.01	2	1.98	2	2.27	2	2.00	2	2.00
2	2.00	1	1.06	2	1.98	2	2.00	3	2.95
2	2.00	3	3.00	2	1.98	2	2.00	2	1.86
2	2.00	2	1.90	2	2.00	1	1.00	3	3.00
2	2.00	1	1.32	2	2.00	2	1.89	1	0.81
3	3.00	1	1.00	2	2.00	2	2.00	1	1.50
2	2.00	1	1.00	2	2.00	2	2.00	2	1.98
2	1.86	3	3.00	2	2.00	2	2.00	2	2.12
2	2.00	1	1.04	1	1.00	2	2.02	2	2.00
2	2.00	2	2.00	2	2.00	3	3.02	2	2.02
2	2.00	2	1.89	2	2.00	2	1.99	2	2.00
2	2.00	4	4.01	2	2.00	1	1.00	2	1.90
2	2.00	2	1.98	2	2.00	1	0.93	2	2.00
2	2.00	2	2.00	2	2.00	2	2.00	2	2.00
2	2.00	2	2.00	2	2.00	3	3.00	2	2.02
2	2.00	1	1.00	2	2.00	3	3.00	2	2.00
2	2.00	2	2.00	2	2.00	2	2.02	2	2.00
2	1.98	1	1.04	2	2.00	2	2.06	3	3.00
2	2.00	2	2.00	2	2.00	1	0.99	1	1.89
2	2.00	2	2.00	2	2.00	1	1.00	2	2.00
2	2.00	2	2.02	2	1.98	2	2.00	2	2.00
2	2.00	2	1.98	2	1.99	2	2.00	2	2.00
2	2.00	2	2.00	2	1.89	2	2.00	1	1.00
2	2.00	2	2.00	3	3.04	2	2.00	2	2.00
2	2.00	2	2.00	2	2.00	2	2.00	2	1.64
2	1.90	1	1.06	2	2.00	2	2.01	2	2.00
2	2.00	2	2.02	2	2.00	1	1.00	2	2.00
2	2.00	2	2.02	1	1.01	1	1.00	2	2.00
2	1.89	2	2.21	1	0.99	2	2.00	2	2.00
3	2.94	2	2.00	2	2.00	2	2.00	2	2.00
2	1.99	2	2.00	2	1.89	2	2.26	2	1.90
2	2.02	2	2.00	2	1.89	2	2.00	2	1.90
2	2.02	2	2.00	3	3.00	2	2.00	2	1.90

Target	ANFIS	Target	ANFIS	Target	ANFIS	Target	ANFIS	Target	ANFIS
2	2.02	2	2.00	2	2.00	3	3.00	4	3.98
2	2.02	2	2.00	1	1.00	3	3.00	1	1.00
2	2.00	2	2.00	2	2.00	2	2.00	2	2.12
2	2.02	2	2.00	1	1.00	2	1.99	-	-
2	2.00	2	2.00	1	1.06	2	1.89	-	-
3	3.00	2	2.00	2	2.00	2	2.01	-	-
2	2.00	1	1.04	2	2.00	2	1.86	-	-
1	1.00	2	2.02	2	2.00	2	2.00	-	-
2	2.00	1	1.04	2	2.00	2	2.00	-	-
2	2.00	3	3.00	2	2.00	4	4.00	-	-
1	1.00	2	2.00	2	2.00	2	2.00	-	-
2	2.26	2	2.00	2	2.00	3	3.00	-	-
2	1.89	2	2.00	2	2.00	2	1.98	-	-
2	2.01	2	2.00	2	2.00	2	2.00	-	-

Out of a total of 239 tests, in 89% of the cases, the predicted rank at the output of the neuro-fuzzy model fully coincides with the real rank achieved at the public tender in 2016. In the remaining 11% there are minor deviations, which are eliminated by rounding to integer values. By analyzing the results we can conclude that the NF-ABC model successfully predicts rank and the results of consulting services. The model provides the possibility of predicting own performance in the market of consulting services. The results obtained can make a good basis for forecasting the success of the observed company in the forthcoming business period, as well as its position on the market. In addition, the predictions provided by the NF-ABC model enable managers to adopt sustainable business strategies in the future.

This research has confirmed two research goals of this paper: (1) it is performed quantification of variables that influence the prediction of ranks of consulting companies participating in public tenders; and (2) it is determined the influence of input variables on the rank of the consulting services providers using neuro-fuzzy model and the ABC algorithm. Specific goal achieved by this paper is the possibility to apply the subject model in other fields of engineering, and not only in construction. This model achieves qualitative planning of further development potentials of companies and understanding and improvement of existing potentials.

The results of the research clearly justify the use of presented model in the decision-making process of the consulting companies. On the one hand, the NF-ABC model is based on a complex mathematical apparatus and, as such, its application can cause an aversion of the management. However, on the other hand, this model allows obtaining credible results when deciding under uncertain conditions. Therefore, the application of this model is significant. Firstly, the NF-ABC model helps managers deal with their own subjectivity when considering the conditions in the environment and the competition. Secondly, with the successful prioritization of the companies, the NF-ABC model reduces uncertainty in the decision-making process. Thirdly, by considering the variables that affect the prediction of company performance, the NF-ABC model significantly reduces uncertainty in business of consulting companies. Finally, the NF-ABC model has the adaptability allowing further modeling based on new real data from the practice. This model provides the management with the most appropriate strategy in accordance with current requirements, while minimizing the risk of decision making.

5. Conclusions

The paper presents a model of strategic management in which the neuro-fuzzy approach and the ABC algorithm are applied. Neuro-fuzzy model is trained with the ABC algorithm and is used to predict the rank of consulting companies when applying for public procurement. The authors' opinion is that this new approach in predicting the success of companies in public procurement is qualitative shift forward in the direction of improving strategic management of the potentials of consulting companies in the construction industry. The NF-ABC model extends theoretical framework of knowledge in the field of decision-support system. The existing problem is considered with the new methodology, which creates the basis for further theoretical, as well as practical upgrading.

This model enables the assessment of future position of consulting companies in the market and the selection of sustainable business strategy in the process of management decision making. This is particularly important in cases where consulting services are provided for the implementation of capital and infrastructure projects with a longer time interval (two years or more). Also, the model presented highlights new criteria for predicting the success of companies that have not been considered in the previous models, and are of importance for this issue. By introducing new criteria and their presentation in the model, it is pointed out the need for their consideration in further analyzes of this and similar issues.

The main disadvantage of the model, arising from the nature of the criteria, is its application only to the company whose data are used for training the model. This would in particular mean that for other companies it is necessary to re-train the model based on their own input and output data.

Future research should be directed towards the identification of additional parameters that affect the rank of companies in line with the specifics of the environment in which the companies operate. This allows directing and controlling strategic development of companies and preventing the development of unwanted situations. In this direction of research, the methods of fuzzy linear and dynamic programming joined with heuristic and meta heuristic methods find their application. One of the recommendations is to consider the rank of companies using genetic algorithms, while defining the limits that are considered by fuzzy linear programming.

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