Complexity

Artificial Neural Networks and Fuzzy Neural Networks for Solving Civil Engineering Problems

Lead Guest Editor: Milos Knezevic
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Editorial Board

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Editorial

Artificial Neural Networks and Fuzzy Neural Networks for Solving Civil Engineering Problems

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Based on the live cycle engineering aspects, such as prediction, design, assessment, maintenance, and management of structures, and according to performance-based approach, civil engineering structures have to fulfill essential requirements for resilience, sustainability, and safety from possible risks, such as earthquakes, fires, floods, extreme winds, and explosions.

The analysis of the performance indicators, which are of great importance for the structural behavior and for the fulfillment of the above-mentioned requirements, is impossible without conducting complex mathematical calculations. Artificial neural networks and Fuzzy neural networks are typical examples of a modern interdisciplinary field which gives the basic knowledge principles that could be used for solving many different and complex engineering problems which could not be solved otherwise (using traditional modeling and statistical methods). Neural networks are capable of collecting, memorizing, analyzing, and processing a large number of data gained from some experiments or numerical analyses. Because of that, neural networks are often better calculation and prediction methods compared to some of the classical and traditional calculation methods. They are excellent in predicting data, and they can be used for creating prognostic models that could solve various engineering problems and tasks. A trained neural network serves as an analytical tool for qualified prognoses of the results, for any input data which have not been included in the learning process of the network. Their usage is reasonably simple and easy, yet correct and precise. These positive effects completely justify their application, as prognostic models, in engineering researches.

The objective of this special issue was to highlight the possibilities of using artificial neural networks and fuzzy neural networks as effective and powerful tools for solving engineering problems. From 12 submissions, 6 papers are published. Each paper was reviewed by at least two reviewers and revised according to review comments. The papers covered a wide range of topics, such as assessment of the real estate market value; estimation of costs and duration of construction works as well as maintenance costs; and prediction of natural disasters, such as wind and fire, and prediction of damages to property and the environment.

I. Marovic et al.'s paper presents an application of artificial neural networks (ANN) in the predicting process of wind speed and its implementation in early warning systems (EWS) as a decision support tool. The ANN prediction model was developed on the basis of the input data obtained by the local meteorological station. The prediction model was validated and evaluated by visual and common calculation approaches after which it was found out that it is applicable and gives very good wind speed predictions. The developed model is implemented in the

EWS as a decision support for the improvement of the existing "procedure plan in a case of the emergency caused by stormy wind or hurricane, snow and occurrence of the ice on the University of Rijeka campus."

The application of artificial neural networks as well as econometric models is characterized by specific advantages and disadvantages. Nevertheless, neural networks have been imposed as a real alternative to econometric methods and as a powerful tool for assessment and forecasting, for example, in the field of evaluating real estate. It is specially emphasized that it is possible to find estimated values instead of exact values. The aim of J. Cetkovic et al.'s research was to construct a prognostic model of the real estate market value in the EU countries depending on the impact of macroeconomic indicators. Based on the available input data—macroeconomic variables that influence the determination of real estate prices, the authors sought to obtain fairly correct output data—prices forecast in the real estate markets of the observed countries.

Offer preparation has always been a specific part of a building process which has a significant impact on company business. Due to the fact that income greatly depends on offer's precision and the balance between planned costs, both direct and overheads, and wished profit, it is necessary to prepare a precise offer within the required time and available resources which are always insufficient. I. Peško et al.'s paper presents research on precision that can be achieved while using artificial intelligence for the estimation of cost and duration in construction projects. Both artificial neural networks (ANNs) and support vector machines (SVM) were analyzed and compared. Based on the investigation results, a conclusion was drawn that a greater accuracy level in the estimation of costs and duration of construction is achieved by using models that separately estimate the costs and the duration. The reason for this lies primarily in the different influence of input parameters on the estimation of costs in comparison with the estimation of duration of the project. By integrating them into a single model, a compromise in terms of the significance of input data is made, resulting in the lower precision of estimation when it comes to ANN models. SVM models feature a greater capacity of generalization, providing at the same time greater accuracy of estimation, both for the estimation of costs and duration of projects as well.

The same problem was treated by M. Juszczyk et al. Their research was on the applicability of ANN for the estimation of construction costs of sports fields. An applicability of multilayer perceptron networks was confirmed by the results of the initial training of a set of various artificial neural networks. Moreover, one network was tailored for mapping a relationship between the total cost of construction works and the selected cost predictors which are characteristic for sports fields. Its prediction quality and accuracy were assessed positively. The research results legitimate the proposed approach.

The maintenance planning within the urban road infrastructure management is a complex problem from both the management and the technoeconomic aspects. The focus of I. Marovic et al.'s research was on decision-making processes related to the planning phase during the management of urban road infrastructure projects. The goal of this research was to design and develop an ANN model in order to achieve a successful prediction of road deterioration as a tool for maintenance planning activities. Such a model was part of the proposed decision support concept for urban road infrastructure management and a decision support tool in planning activities. The input data were obtained from Circly 6.0 Pavement Design Software and used to determine the stress values. It was found that it is possible and desirable to apply such a model in the decision support concept in order to improve urban road infrastructure maintenance planning processes.

The fire resistance of civil engineering structures can be determined based on the estimated fire resistance of each construction element (columns, beams, slabs, walls, etc.). As fire resistance of structural elements directly affects the functionality and safety of the whole structure, the significance which new methods and computational tools have on enabling a quick, easy, and simple prognosis of the same, is quite clear. M. Lazarevska et al.'s paper considered the application of fuzzy neural networks by creating prognostic models for determining fire resistance of eccentrically loaded reinforced concrete columns. Using the concept of the fuzzy neural networks and the results of the performed numerical analyses (as input parameters), the prediction model for defining the fire resistance of eccentrically loaded RC columns incorporated in walls and exposed to standard fire from one side has been made. The numerical results were used as input data in order to create and train the fuzzy neural network so it can provide precise outputs for the fire resistance of eccentrically loaded RC columns for any other input data (RC columns with different dimensions of the cross-section, different thickness of the protective concrete layer, different percentage of reinforcement and for different loads).

These papers represent an exciting, insightful observation into the state of the art as well as emerging future topics in this important interdisciplinary field. We hope that this special issue would attract a major attention of the civil engineering's community.

We would like to express our appreciation to all the authors and reviewers who contributed to publishing this special issue.

Conflicts of Interest

As guest editors, we declare that we do not have a financial interest regarding the publication of this special issue.

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Research Article

Determination of Fire Resistance of Eccentrically Loaded Reinforced Concrete Columns Using Fuzzy Neural Networks

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Artificial neural networks, in interaction with fuzzy logic, genetic algorithms, and fuzzy neural networks, represent an example of a modern interdisciplinary field, especially when it comes to solving certain types of engineering problems that could not be solved using traditional modeling methods and statistical methods. They represent a modern trend in practical developments within the prognostic modeling field and, with acceptable limitations, enjoy a generally recognized perspective for application in construction. Results obtained from numerical analysis, which includes analysis of the behavior of reinforced concrete elements and linear structures exposed to actions of standard fire, were used for the development of a prognostic model with the application of fuzzy neural networks. As fire resistance directly affects the functionality and safety of structures, the significance which new methods and computational tools have on enabling quick, easy, and simple prognosis of the same is quite clear. This paper will consider the application of fuzzy neural networks by creating prognostic models for determining fire resistance of eccentrically loaded reinforced concrete columns.

1. Introduction

The fire resistance of civil engineering structures can be determined based on the estimated fire resistance of each construction element (columns, beams, slabs, walls, etc.). The fire resistance of a structural element is the time period (in minutes) from the start of the fire until the moment when the element reaches its ultimate capacity (ultimate strength, stability, and deformability) or until the element loses the insulation and its separation function [1]. The legally prescribed values for the fire resistance can be achieved by application of various measures (by using appropriate shape and element's dimensions and proper static system, thermo-isolation, etc.). The type of applied protection measures mainly depend on the type of construction material that needs to be protected. Different construction materials (concrete, steel, and wood) have different behaviors under elevated temperatures. That is why they have to be protected in accordance with their individual characteristics when exposed to fire [1]. Even though the legally prescribed values of the fire resistance is of huge importance for the safety of every engineering structures, in Macedonia there is no explicit legally binding regulation for the fire resistance. The official national codes in the Republic of Macedonia are not being upgraded, and the establishment of new codes is still a continuing process. Furthermore, most of the experimental models for determination of fire resistance are extremely expensive, and analytical models are quite complicated and time-consuming. A modern type of analyses, such as modeling through neural networks, can be very helpful, particularly in those cases where some prior analyses were already made. Therefore, the application of artificial and

fuzzy neural networks for prognostic modeling of the fire resistance of structures is of significant importance, especially during the design phase of civil engineering structures.

Fuzzy neural networks are typical example of a modern interdisciplinary subject that helps solving different engineering problems which cannot be solved by the traditional modeling methods [2–4]. They are capable of collecting, memorizing, analyzing, and processing large number of data obtained from some experiments or numerical analyses. The trained fuzzy neural network serves as an analytical tool for precise predictions, for any input data which are not included in the training or testing process of the model. Their operation is reasonably simple and easy, yet correct and precise.

Using the concept of the fuzzy neural networks and the results of the performed numerical analyses (as input parameters), the prediction model for defining the fire resistance of eccentrically loaded RC columns incorporated in walls and exposed to standard fire from one side has been made.

The goal of the research presented in this paper was to build a prognostic model which could generate outputs for the fire resistance of RC columns incorporated in walls, for any given input data, by using the results from the conducted numerical analyses. The numerical results were used as input data in order to create and train the fuzzy neural network so it can provide precise outputs for the fire resistance of eccentrically loaded RC columns for any other input data (RC columns with different dimensions of the cross section, different thickness of the protective concrete layer, different percentage of reinforcement, and for different loads).

2. Fuzzy Neural Networks: Theoretical Basis

Fuzzy neural networks are defined as a combination of artificial neural networks and fuzzy systems, in such a way that learning algorithms from neural networks are used to determine the parameters of a fuzzy system. One of the most important aspects of this combination is that the system can always be interpreted using the "if-then" rule, because it is based on a fuzzy system that reflects uncertain/unclear knowledge. Fuzzy neural networks use linguistic knowledge from the fuzzy system and learning ability from neural networks. Therefore, fuzzy neural networks are capable of precisely modeling ambiguity, imprecision, and uncertainty of data, with the additional learning opportunity characteristic of neural networks [3, 5–8].

Fuzzy neural networks are based on a common concept of fuzzy logic and artificial neural networks, theories that are already at the top of the list for researchers of artificial intelligence. Fuzzy logic, based on Zadeh's principle of fuzzy sets, provides mathematical potential for describing the uncertainty that is associated with cognitive processes of thinking and reasoning. This makes it possible to draw conclusions even with incomplete and insufficiently precise information (so-called approximate conclusions). On the other hand, artificial neural networks with their various architectures built on the artificial neuron concept have been developed as an imitation of the biological neural system for the successful performance of learning and recognition functions. What is expected from the fusion of these two structures is that the learning and computational ability of neural networks will be transmitted into the fuzzy system and that the highly productive if-then thinking of the fuzzy system will be transferred to neural networks. This would allow neural networks to be more than simply "black boxes," while fuzzy inference systems will be given the opportunity to automatically adjust their parameters [2, 3, 5–8].

Depending on the field of application, several approaches have been developed for connecting artificial neural networks and fuzzy inference systems, which are most often classified into the following three groups [3, 5, 7–9]: cooperative models, concurrent models, and integrated (hybrid) models.

The basic characteristic of the cooperative model is that via learning mechanisms of artificial neural networks, parameters of the fuzzy inference system are determined through training data, which allows for its quick adaption to the problem at hand. A neural network is used to determine the membership function of the fuzzy system, the parameters for fuzzy rules, weight coefficients, and other necessary parameters. Fuzzy rules are usually determined using clustering access (self-organizing), while membership functions are elicited from training data using a neural network [3, 5, 7–9].

Characteristic of the concurrent model is that the neural network continuously assists the fuzzy inference system during the process of determining and adjusting required parameters. In some cases, the neural network can correct output results, while in other cases, it corrects input data into the fuzzy inference system [3, 5, 7–9].

For integrated fuzzy neural networks, the learning algorithm from a neural network is used to determine the parameters of the fuzzy inference system. These networks represent a modern class of fuzzy neural networks characterized by a homogeneous structure, that is, they can be understood as neural networks represented by fuzzy parameters [3, 5–9]. Different models for hybrid fuzzy neural networks have been developed, among which the following stand out: FALCON, ANFIS, GARIC, NEFCON, FUN, SONFIN, FINEST, and EFuNN.

3. State-of-the-Art Application of Fuzzy Neural Networks

In the civil engineering field, fuzzy neural networks are very often used to predict the behavior of materials and constructive elements. The main goal of such prognostic models is to obtain a solution to a problem by prediction (mapping input variables into corresponding output values). For the qualitative development of efficient prognostic models, it is necessary to have a number of data groups. Fortunately, when it comes to civil engineering, data collection is not a major problem, which enhances the possibility of applying such innovative techniques and methods. Some examples of successful application of fuzzy neural networks to various fields of civil engineering are presented in the following section of this paper [4, 5].

Fuzzy neural networks have enjoyed successful implementation in civil engineering project management. Boussabaine and Elhag [10] developed a fuzzy neural

network for predicting the duration and cost of construction works. Yu and Skibniewski (1999) investigated the application of fuzzy neural networks and genetic algorithms in civil engineering. They developed a methodology for the automatic collection of experiential data and for detecting factors that adversely affect building technology [11]. Lam et al. [12] successfully applied the principles of fuzzy neural networks towards creating techniques for modeling uncertainty, risk, and subjectivity when selecting contractors for the construction works. Ko and Cheng [13] developed an evolutionary fuzzy neural inference model which facilitates decision-making during construction project management. They tested this model using several practical examples: during the selection of subcontractors for construction works and for calculating the duration of partition wall construction, an activity that has an excessive impact on the completion of the entire project. Jassbi and Khanmohammadi applied ANFIS to risk management [14]. Cheng et al. proposed an improved hybrid fuzzy neural network for calculating the initial cost of construction works [15]. Rashidi et al. [16] applied fuzzy neural systems to the selection of project managers for construction projects. Mehdi and Reza [17] analyzed the application of ANFIS for determining risks in construction projects, as well as for the development of intelligent systems for their assessment. Feng and Zhu [18] developed a model of self-organizing fuzzy neural networks for calculating construction project costs. Feylizadeh et al. [19] used a model of fuzzy neural networks to calculate completion time for construction works and to accurately predict different situations.

Fuzzy neural networks are also used for an analysis of structural elements and structures. Ramu and Johnson applied the approach of integrating neural networks and fuzzy logic for assessing the damage to composite structures [20]. Liu and Wei-guo (2004) investigated the application of fuzzy neural networks towards assessing the safety of bridges [21]. Foncesa used a fuzzy neural system to predict and classify the behavior of girders loaded with concentrated loads [22]. Wang and Liu [23] carried out a risk assessment in bridge structures using ANFIS. Jakubek [24] analyzed the application of fuzzy neural networks for modeling building materials and the behavior of structures. The research encompassed an analysis of three problems: prediction of fracture in concrete during fatigue, prediction of high performance concrete strength, and prediction of critical axial stress for eccentrically loaded reinforced concrete columns. Tarighat [25] developed a fuzzy neural system for assessing risk and damage to bridge structures, which allows important information to be predicted related to the impact of design solutions on bridge deterioration. Mohammed [26] analyzed the application of fuzzy neural networks in order to predict the shear strength of ferrocement elements and concrete girders reinforced with fiber-reinforced polymer tapes.

Cüneyt Aydin et al. developed a prognostic model for calculating the modulus of elasticity for normal dams and high-strength dams with the help of ANFIS [27]. Tesfamariam and Najjaran applied the ANFIS model to calculate the strength of concrete [28]. Ozgan et al. [29] developed an adaptive fuzzy neural system (ANFIS) Sugeno type for predicting stiffness parameters for asphalt concrete.

Chae and Abraham assessed the state of sewage pipelines using a fuzzy neural approach [30]. Adeli and Jiang [4] developed a fuzzy neutral model for calculating the capacity of work areas near highways. Nayak et al. modeled the connection and the interaction of soil and structures with the help of fuzzy neural networks. Nayak et al. [31] applied ANFIS to the hydrological modeling of river flows, that is, to the forecasting of time-varying data series.

Cao and Tian proposed the ANFIS model for predicting the need for industrial water [32]. Chen and Li made a model for the quality assessment of river water using the fuzzy neural network methodology [33]. F.-J. Chang and Y.-T. Chang applied a hybrid fuzzy neural approach for constructing a system for predicting the water level in reservoirs [34]. More precisely, they developed a prognostic ANFIS model for the management of accumulations, while the obtained results showed that it could successfully be applied to, precisely and credibly, predict the water level in reservoirs. Jianping et al. (2007) developed an improved model of fuzzy neural networks for analysis and deformation monitoring of dam shifts. Hamidian and Seyedpoor have used the methodology for fuzzy neural networks to determine the optimal shape of arch dams, as well as for predicting an effective response to the impact of earthquakes [35]. Thipparat and Thaseepetch applied the Sugeno type of ANFIS model so as to assess structure sustainability of highways in order to obtain relevant information about environmental protection [36].

An increased interest in the application of fuzzy neural networks to civil engineering can be seen in the last few decades. A comprehensive review of scientific papers which have elaborated on this issue published in scientific journals from 1995 until 2017 shows that fuzzy neural networks are mainly used to address several categories of problems: modeling and predicting, calculating and evaluating, and decision-making. The results of the conducted analysis illustrate the efficiency and practicality of applying this innovative technique towards the development of models for managing, decision-making, and assessing problems encountered when planning and implementing construction works. Their successful implementation represents a pillar for future research within the aforementioned categories, although the future application of fuzzy neural networks can be extended to other areas of civil engineering as well.

4. Prognostic Modeling of the Fire Resistance of Eccentrically Loaded Reinforced Concrete Columns Using Fuzzy Neural Networks

Eccentrically loaded columns are most commonly seen as the end columns in frame structures, and they are inserted in the partition walls that separate the structure from the surrounding environment or separating the fire compartment under fire conditions. The behavior of these types of columns, when exposed to fire, and the analysis of the influence of special

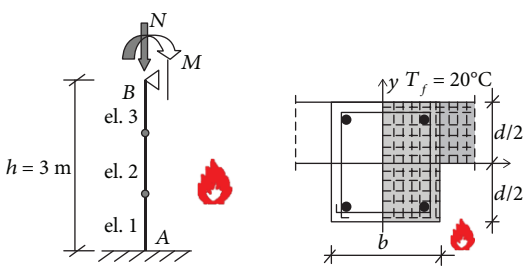

Figure 1: RC column inserted into the fire separation wall.

factors on their fire resistance have been analyzed in literature [37, 38].

Numerical analysis was carried out for the reinforced concrete column (Figure 1) exposed to standard fire ISO 834 [27]. Due to axial symmetry, only one-half of the cross section was analyzed [37, 38]. The following input parameters were analyzed: the dimensions of the cross section, the intensity of initial load, the thickness of the protective concrete layer, the percentage of reinforcement, and the type of concrete (siliceous or carbonate). The output analysis result is the time period of fire resistance expressed in hours [37, 38].

The results from the numerical analysis [37] were used to create a prognostic model for determining the fire resistance of eccentrically loaded reinforced concrete columns in the fire compartment wall.

The application of fuzzy neural networks for the determination of fire resistance of eccentrically loaded reinforced concrete columns is presented below.

The prognostic model was developed using adaptive fuzzy neural networks—ANFIS in MathWorks software using an integrated Fuzzy Logic Toolbox module [39].

ANFIS represents an adaptive fuzzy neural inference system. The advantage of this technique is that membership functions of input parameters are automatically selected using a neuroadaptive training technique incorporated into the Fuzzy Logic Toolbox. This technique allows the fuzzy modeling process to learn from the data. This is how parameters of membership functions are calculated through which the fuzzy inference system best expresses input-output data groups [39].

ANFIS represents a fuzzy neural feedforward network consisting of neurons and direct links for connecting neurons. ANFIS models are generated with knowledge from data using algorithms typical of artificial neural networks. The process is presented using fuzzy rules. Essentially, neural networks are structured in several layers through which input data and fuzzy rules are generated. Similar to fuzzy logic, the final result depends on the given fuzzy rules and membership functions. The basic characteristic of ANFIS architecture is that part, or all, of the neurons is flexible, which means that their output depends on system parameters, and the training rules determine how these parameters are changed in order to minimize the prescribed error value [40].

ANFIS architecture consists of 5 layers and is illustrated in Figure 2 [3, 5–7, 40].

The first (input) layer of the fuzzy neural network serves to forward input data to the next layer [3, 5–7, 40].

The second layer of the network (the first hidden layer) serves for the fuzzification of input variables. Each neuron within this layer is represented by the function: $O_i^1 = \mu_{Ai}(x)$, where x denotes entrance into the neuron i and A_i denotes linguistic values. O_i^1 is in fact a membership function in A_i indicating how many entrances X_i satisfy a quantifier A_i^j. The parameters of this layer represent the parameters of the fuzzy rule premise [3, 5–7, 40].

The third layer (the second hidden layer) of the network consists of the T-norm operator for the calculation of fuzzy rule premise. Neurons are denoted as π, which represents a designation for the product of all input signals: $w_i = \mu_{Ai}(x) \times \mu_{Bi}(y)$. Each neuron from this layer establishes the rule strength of fuzzy rules [3, 5–7, 40].

The fourth network layer (the third hidden layer) normalizes the rule strength. In each neuron, the relationship between the rule strength of the associated rule and the sum of all strengths is calculated: $\overline{w_i} = w_i / \sum w_i$ [3, 5–7, 40].

The procedure for determining subsequent parameters (conclusions) from fuzzy rules is carried out in the fifth layer (the fourth hidden layer). Each node from this layer is a square (adaptive) node marked by the function $O_i^4 = \overline{w_i} Z_i = \overline{w_i}(p_i X + q_i Y + r_i)$, where $\{p_i, q_i, r_i\}$ are conclusion parameters and w_i is the output from the previous layer.

The output layer contains one neuron denoted by the letter Σ due to the summing function. It calculates the total output as the sum of all input signals, in the function of premise parameters and fuzzy rule conclusions: $O_i^5 = \sum \overline{w_i} Z_i = \sum w_i Z_i / \sum w_i$ [3, 5–7, 40].

For a fuzzy neural network consisting of 2 input variables and 2 fuzzy rules (Figure 2), the total output would be calculated as follows [3, 5–7, 40]:

$$\begin{aligned} Z &= \sum \overline{w_i} Z_i = \frac{\sum w_i Z_i}{\sum w_i} = \frac{w_1}{w_1 + w_2} Z_1 + \frac{w_2}{w_1 + w_2} Z_1 \\ &= \overline{w_1} Z_1 + \overline{w_2} Z_2 = \overline{w_1}(p_1 X + q_1 Y + r_1) \\ &\quad + \overline{w_2}(p_2 X + q_2 Y + r_2), \end{aligned} \tag{1}$$

where (X, Y) is the numerical input of the fuzzy neural network, Z is the numerical output of the fuzzy neural network, $(\overline{w_1}, \overline{w_2})$ are the normalized rule strengths of fuzzy rules expressed through the fuzzy rule premise, and $(p_1, q_1, r_1, p_2, q_2, r_2)$ are the parameters of the fuzzy rule conclusions.

The ANFIS training algorithm consists of two segments: reverse propagation method (backpropagation algorithm), which determines errors of variables from a recursive path, from the output to the input layers, determining variable errors, that is, parameters of the membership function, and the least square method determining the optimal set of consequent parameters. Each step in the training procedure consists of two parts. In the first part, input data is propagated and optimal consequent parameters are estimated using the iterative least-mean-square method, while fuzzy rule premise parameters are assumed to be fixed for the current cycle through the training set. In the second part, input data is propagated again, but in this process, the

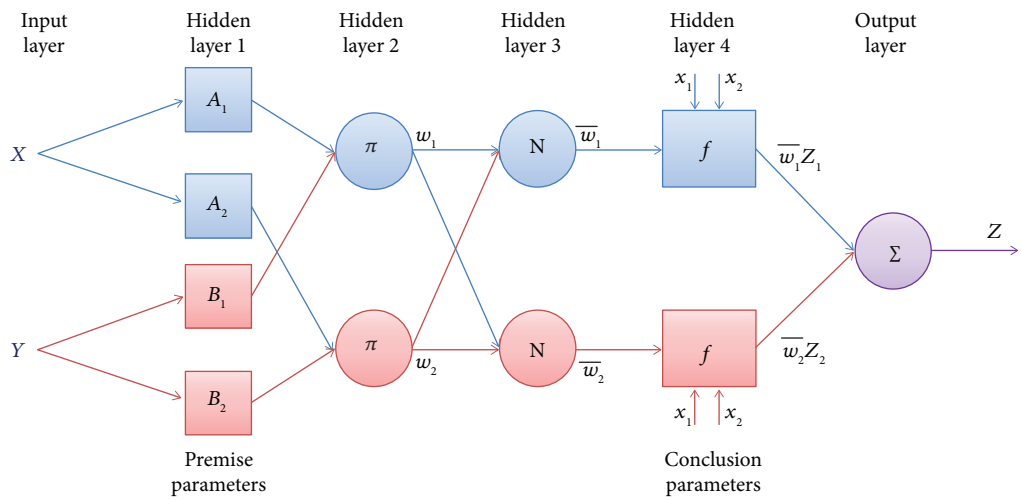

Figure 2: An overview of the ANFIS network.

backpropagation algorithm is used to modify the premise parameter while the consequent parameters remain fixed. This procedure is iterated [3, 5–7, 40].

For the successful application of ANFIS during the process of solving a specific problem task, it is necessary to possess solid professional knowledge of the problem at hand and appropriate experience. This enables a correct and accurate choice of input variables, that is, unnecessarily complicating the model by adding nonsignificant variables, or not including important parameters that have a significant effect on output values, is avoided.

The application of fuzzy neural network techniques to the modeling process is carried out in a few steps [39, 41]: assembling and processing data, determining the parameters and structure of the fuzzy neural network (creating the fuzzy inference system), training the fuzzy neural network, and testing the fuzzy neural network and prognostics.

For the purpose of prognostic modeling of the eccentrically loaded RC columns, the structure of the fuzzy neural network consists of 6 input variables (dimensions of the reinforced concrete column (b and d), thickness of the protective concrete layer (a), percentage of reinforcement (μ), axial load coefficient (η), bending moment coefficient (β), and one output variable (fire resistance of the reinforced concrete column (t)).

One of the most crucial aspects, when using a fuzzy neural networks as prognostic modeling technique, is to collect accurate and appropriate data sets. The data has to contain a finite number of sets where each data set has to be defined with an exact input and output values. Another very important aspect is to have large amount of data sets. Data sets are divided into two main groups: data used for training of the model and data used for testing of the model prediction accuracy. The training data should contain all the necessary representative features, so the process of selecting a data set for checking or testing purposes is made easier. One problem for models constructed using adaptive techniques is selecting a data set that is both representative of the data the trained model is intended to imitate, yet sufficiently distinct from the training data set so as not to render the validation process trivial. To design an ANFIS system for real-world problems, it is essential to select the parameters for the training process. It is essential to have proper training and testing data sets. If the data sets are not selected properly, then the testing data set will not validate the model. If the testing data set is completely different from the training data set, then the model cannot capture any of the features of the testing data. Then, the minimum testing error can be achieved in the first epoch. For the proper data set, the testing error decreases with the training proceeding until a jump point. The selection of data sets for training and testing of the ANFIS system is an important factor affecting the performance of the model. If the data sets used for testing is extremely different from one of the training data sets, then the system fails to capture the essential features of the data set. Another aspect that has to be emphasized is that all data sets have to be properly selected, adequately collected, and exact. The basic characteristic of all computer programs used for calculation and modeling applies for the neural networks as well: only quality input can give a quality output! Even though neural networks represent an intelligent modeling technique, they are not omnipotent, which means that if the input data sets are not clear and correct, the neural network model will not be able to produce accurate output results.

A training data group is used to initially create a model structure [39]. The training process is a learning process of the developed model. The model is trained till the results are obtained with minimum error. During the learning process, the parameters of the membership functions are updated. In MATLAB, the two ANFIS parameter optimization methods are hybrid (combination of least squares and back propagation method) and back propagation. Error tolerance is used as training stopping criterion, which is related to the error size. The training will stop after the training data error remains within this tolerance. The training error is the difference between the training data output value and the output of the fuzzy inference system corresponding to the same training data input value (the one associated with that training data output value).

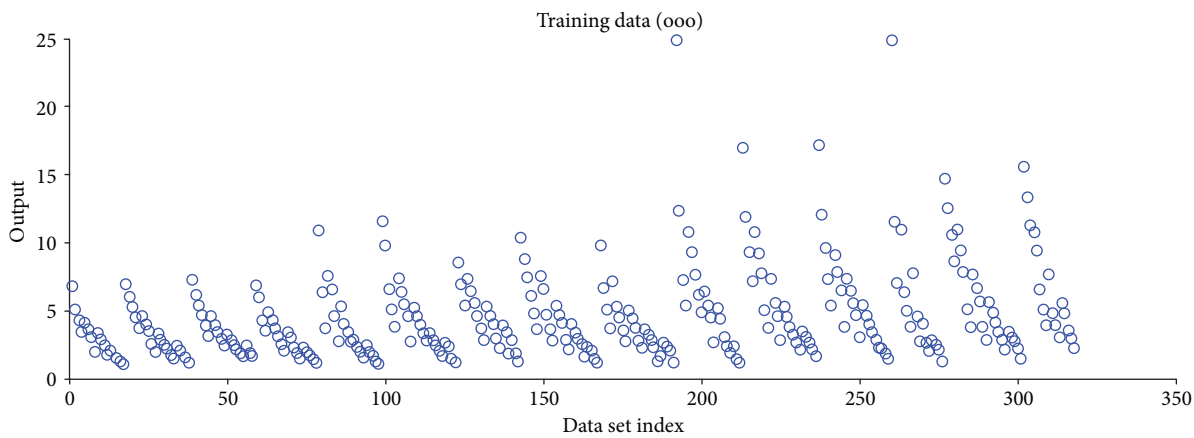

Figure 3: Graphical representation of the training data loaded into ANFIS.

The data groups used for checking and testing of the model are also referred as validation data and are used to check the capabilities of the generalization model during training [39]. Model validation is the process by which the input data sets on which the FIS was not trained are presented to the trained FIS model, to see the performance. The validation process for the ANFIS model is carried out by leaking vectors from the input-output testing data into the model (data not belonging to the training group) in order to verify the accuracy of the predicted output. Testing data is used to validate the model. The testing data set is used for checking the generalization capability of the ANFIS model. However, it is desirable to extract another group of input-output data, that is, checking data, in order to avoid the possibility of an "overfitting." The idea behind using the checking data stems from the fact that a fuzzy neural network may, after a certain number of training cycles, be "overtrained," meaning that the model practically copies the output data instead of anticipating it, providing great predictions but only for training data. At that point, the prediction error for checking data begins to increase when it should exhibit a downward trend. A trained network is tested with checking data, and parameters for membership functions are chosen for which minimal errors are obtained. These data controls this phenomenon by adjusting ANFIS parameters, with the aim of achieving the least errors in prediction. However, when selecting data for model validation, a detailed database study is required because the validation data should be not only sufficiently representative of the training data but also sufficiently different to avoid marginalization of training [39, 41].

Even though there are many published researches worldwide that investigate the impact of the proportion of data used in various subsets on neural network model, there is no clear relationship between the proportion of data for training, testing and validation, and model performance. However, many authors recommend that the best result can be obtained when 20% of the data are used for validation and the remaining data are divided into 70% for training and 30% for testing. The number of training and testing data sets greatly depends on the total number of data sets. So, the real apportion of train and test data set is closely related with the real situation, problem specifics, and the quantity of the data set. There are no strict rules regarding the data set division, so when using the adaptive modeling techniques, it is very important to know how well the data sets describe the features of the problem and to have a decent amount of experience and knowledge about neural networks [42, 43].

The database used for ANFIS modeling, for the model presented in this paper, expressed through input and output variables, was obtained from a numerical analysis. A total of 398 input-output data series were analyzed, out of which 318 series (80%) were used for network training, and 80 series (20%) were data for testing the model. The prediction of the output result was performed on new 27 data sets. The three data groups loaded into ANFIS are presented in Figures 3–5.

For a precise and reliable prediction of fire resistance for eccentrically loaded reinforced concrete columns, different ANFIS models were analyzed with the application of the subtractive clustering method and a hybrid training mode.

The process of training fuzzy neural networks involves adjusting the parameters of membership functions. Training is an iterative process that is carried out on training data sets for fuzzy neural networks [39]. The training process ends when one of the two defined criteria has been satisfied; these are error tolerance percentage and number of iterations. For the analysis in this research, the values of these criteria were 0 for error tolerance and 100 for number of training iterations.

After a completed training process of the generated ANFIS model, it is necessary to validate the model using data sets defined for testing and checking [39, 44]: the trained model is tested using validation data, and the obtained average errors and the estimated output values are analyzed.

The final phase of the modeling using fuzzy neural networks is prognosis of outputs and checking the model's prediction accuracy. To this end, input data is passed through the network to generate output results [39, 44]. If low values of average errors have been obtained during the testing and validation process of the fuzzy neural network, then it is quite certain that a trained and validated ANFIS model can be applied for a high-quality and precise prognosis of output values.

For the analyzed case presented in this paper, the optimal ANFIS model is determined by analyzing various fuzzy

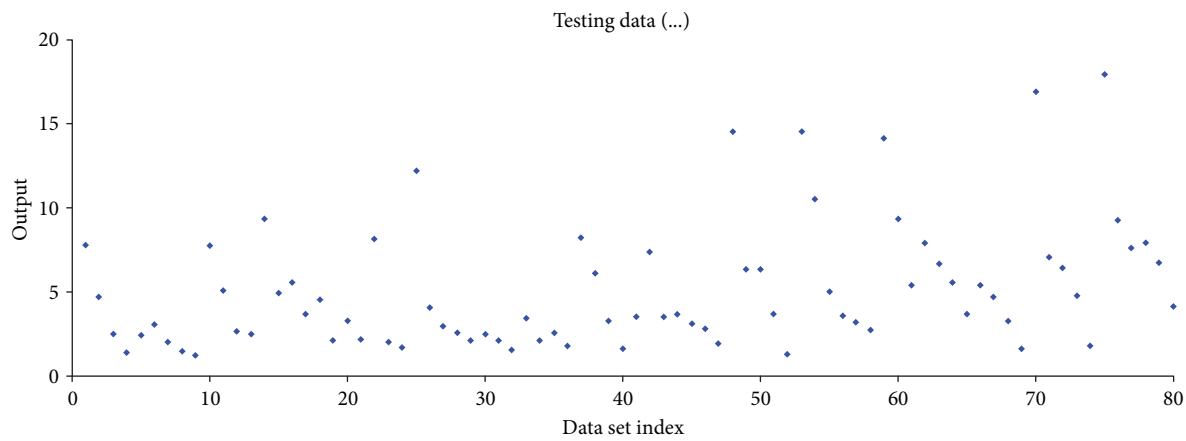

Figure 4: Graphical representation of the test data loaded into ANFIS.

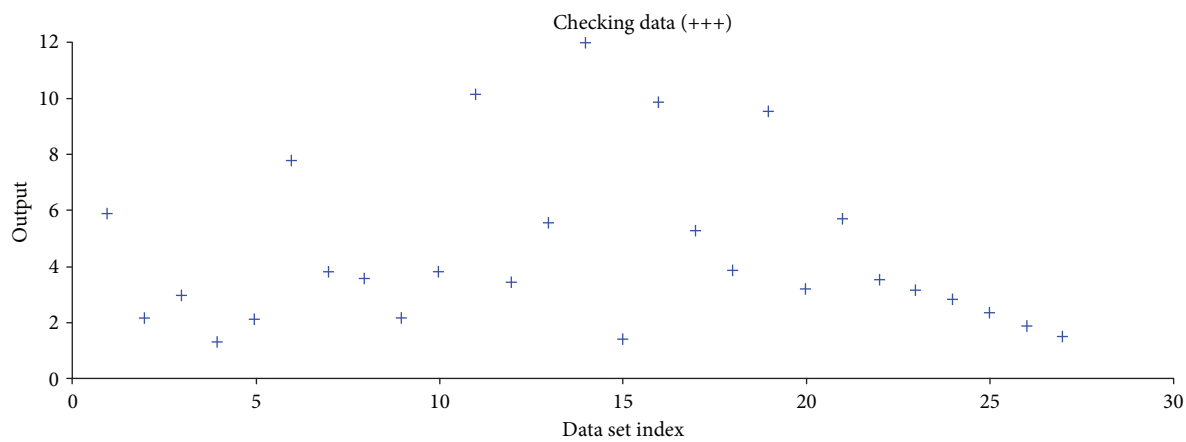

Figure 5: Graphical representation of the checking data loaded into ANFIS.

neural network architectures obtained by varying the following parameters: the radius of influence (with values from 0.6 to 1.8) and the compaction factor (with values in the interval from 0.45 to 2.5). The mutual acceptance ratio and the mutual rejection ratio had fixed values based on standard values defined in MATLAB, amounting to 0.5 and 0.15 [39]. A specific model of the fuzzy neural network, with a designation depending on the parameter values, was created for each combination of these parameters. The optimal combination of parameters was determined by analyzing the behavior of prognostic models and by comparing obtained values for average errors during testing and predicting output values. Through an analysis of the results, it can be concluded that the smallest value for average error in predicting fire resistance of eccentrically loaded reinforced concrete columns is obtained using the FIS11110 model with Gaussian membership function (gaussMF) for the input variable and linear output function, with 8 fuzzy rules. The average error during model testing was 0.319 for training data, 0.511 for testing data, and 0.245 for verification data.

Figure 6 gives a graphical representation of the architecture of the adopted ANFIS model, composed of 6 input

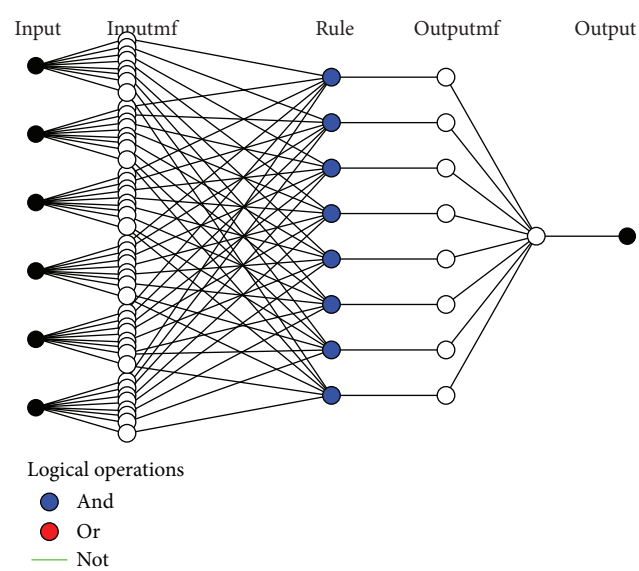

Figure 6: Architecture of ANFIS model FIS11110 composed of 6 input variables and 1 output variable.

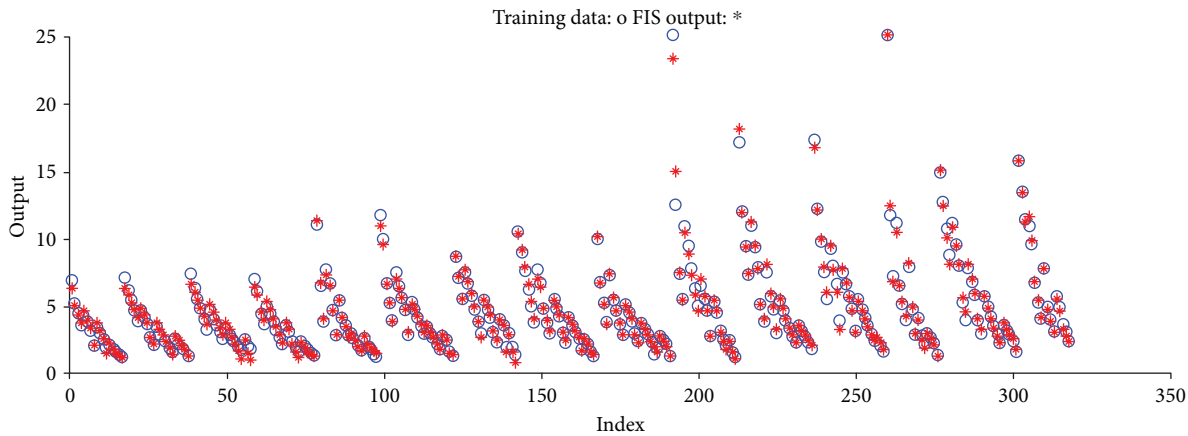

Figure 7: Comparison of the actual and predicted values of fire resistance time for RC columns obtained with ANFIS training data.

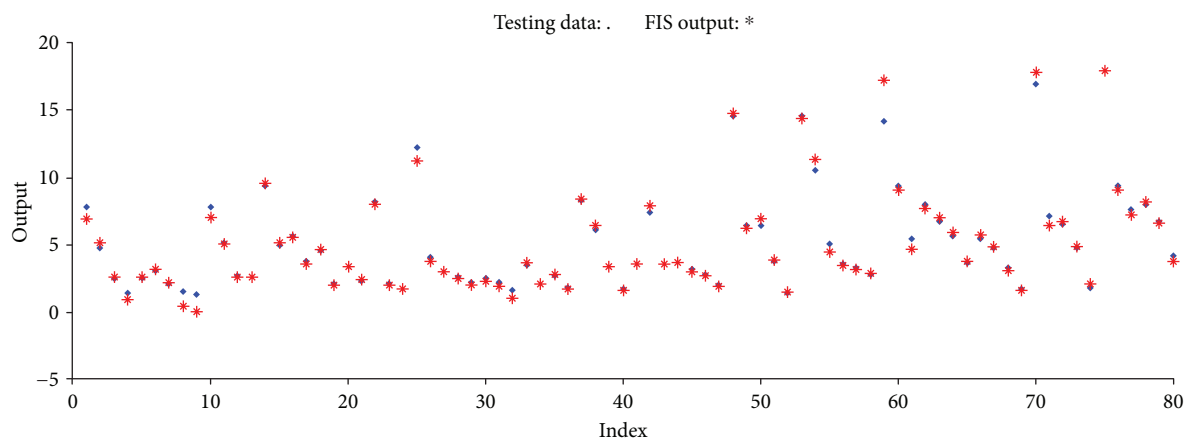

Figure 8: A comparison of actual and predicted values of fire resistance time for RC columns obtained from the ANFIS testing data.

variables defined by Gaussian membership functions and 1 output variable.

The training of the ANFIS model was carried out with 318 input-output data groups. A graphic representation of fire resistance for the analyzed reinforced concrete columns obtained by numerical analysis [37] and the predicted values obtained by the FIS11110 prognostic model for the training data is given in Figure 7.

It can be concluded that the trained ANFIS prognostic model provides excellent results and quite accurately predicts the time of fire resistance of the analyzed reinforced concrete, for input data that belong to the size intervals the network was trained for—the analyzed 318 training cases. The average error that occurs when testing the network using training data is 0.319.

The testing of the ANFIS model was carried out using 80 input/output data sets. A graphical comparison representation of the actual and predicted values of fire resistance for analyzed reinforced concrete columns, for the testing data sets, is presented in Figure 8.

Figures 7 and 8 show an excellent match between predicted values obtained from the ANFIS model with the actual values obtained by numerical analysis [37]. The average error that occurs when testing the fuzzy neural network using testing data is 0.511.

Figure 9 presents the fuzzy rules, as part of the Fuzzy Logic Toolbox program, of the trained ANFIS model FIS11110. Each line in the figure corresponds to one fuzzy rule, and the input and output variables are subordinated in the columns. Entering new values for input variables automatically generates output values, which very simply predicts fire resistance for the analyzed reinforced concrete columns.

The precision of the ANFIS model was verified using 27 input-output data groups (checking data), which also represents a prognosis of the fuzzy neural network because they were not used during the network training and testing. The obtained predicted values for fire resistance for the analyzed reinforced concrete columns are presented in Table 1. A graphic representation of the comparison between actual values (obtained by numerical analysis [37]) and predicted values (obtained through the ANFIS model FIS11110) for fire resistance of eccentrically loaded reinforced concrete columns in the fire compartment wall is presented in Figure 10.

An analysis of the value of fire resistance for the analyzed eccentrically loaded reinforced concrete columns shows that the prognostic model made with fuzzy neural networks

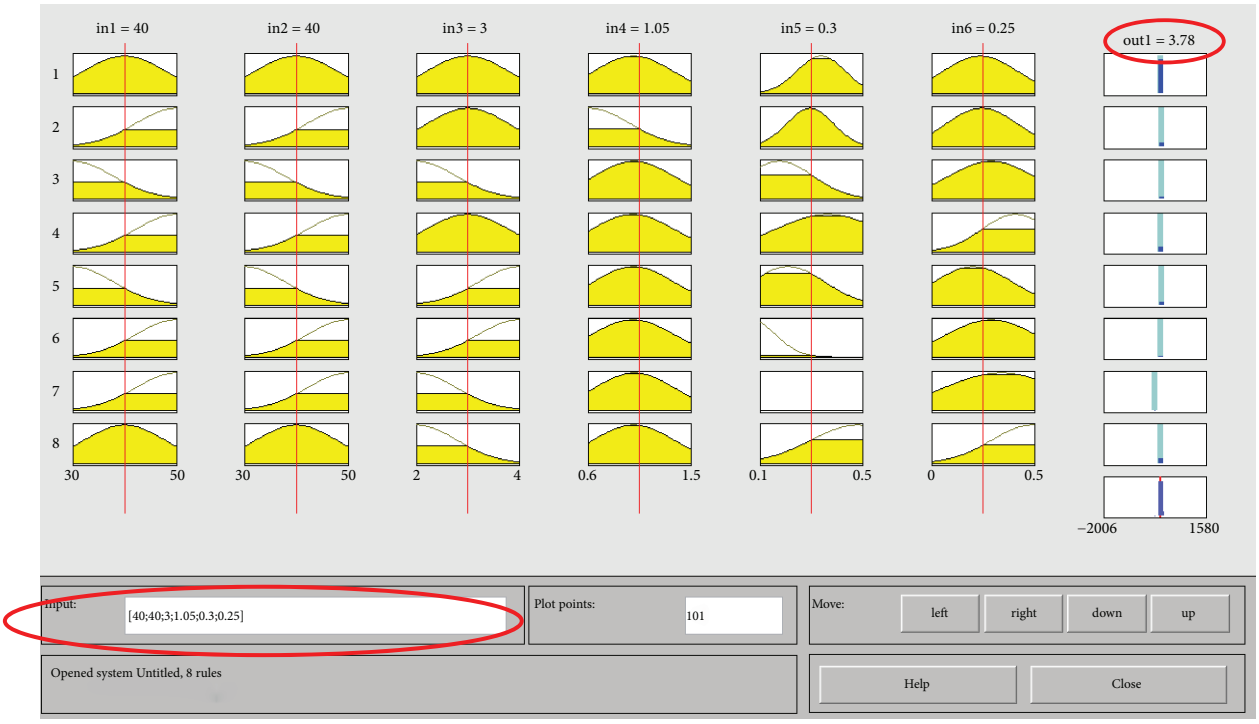

Figure 9: Illustration of fuzzy rules for the ANFIS model FIS11110.

provides a precise and accurate prediction of output results. The average square error obtained when predicting output results using a fuzzy neural network (ANFIS) is 0.242.

This research indicates that this prognostic model enables easy and simple determination of fire resistance of eccentrically loaded reinforced concrete columns in the fire compartment wall, with any dimensions and characteristics.

Based on a comparison of results obtained from a numerical analysis and results obtained from the prognostic model made from fuzzy neural networks, it can be concluded that fuzzy neural networks represent an excellent tool for determining (predicting) fire resistance of analyzed columns. The prognostic model is particularly useful when analyzing columns for which there is no (or insufficient) previous experimental and/or numerically derived data, and a quick estimate of its fire resistance is needed. A trained fuzzy neural network gives high-quality and precise results for the input data not included in the training process, which means that a projected prognostic model can be used to estimate reinforced concrete columns of any dimension and characteristic (in case of centric load). It is precisely this positive fact that fully justifies the implementation of more detailed and extensive research into the application of fuzzy neural networks for the design of prognostic models that could be used to estimate different parameters in the construction industry.

5. Conclusion

Prognostic models based on the connection between popular methods for soft computing, such as fuzzy neural networks, use positive characteristics of neural networks and fuzzy systems. Unlike traditional prognostic models that work precisely, definitely, and clearly, fuzzy neural models are capable of using tolerance for inaccuracy, uncertainty, and ambiguity. The success of the ANFIS is given by aspects like the designated distributive inferences stored in the rule base, the effective learning algorithm for adapting the system's parameters, or by the own learning ability to fit an irregular or nonperiodic time series. The ANFIS is a technique that embeds the fuzzy inference system into the framework of adaptive networks. The ANFIS thus draws the benefits of both ANN and fuzzy techniques in a single framework. One of the major advantages of the ANFIS method over fuzzy systems is that it eliminates the basic problem of defining the membership function parameters and obtaining a set of fuzzy if-then rules. The learning capability of ANN is used for automatic fuzzy if-then rule generation and parameter optimization in the ANFIS. The primary advantages of the ANFIS are the nonlinearity and structured knowledge representation. Research and applications on fuzzy neural networks made clear that neural and fuzzy hybrid systems are beneficial in fields such as the applicability of existing algorithms for artificial neural networks (ANNs), and direct adaptation of knowledge articulated as a set of fuzzy linguistic rules. A hybrid intelligent system is one of the best solutions in data modeling, where it is capable of reasoning and learning in an uncertain and imprecise environment. It is a combination of two or more intelligent technologies. This combination is done usually to overcome single intelligent technologies. Since ANFIS combines the advantages of both neural network and fuzzy logic, it is capable of handling complex and nonlinear problems.

The application of fuzzy neural networks, as an unconventional approach, for prediction of the fire resistance of

Table 1: Actual and predicted value of fire resistance time for RC columns obtained with the ANFIS checking data.

Checking data							
Column dimensions		Thickness of the protective concrete layer	Percentage of reinforcement	Axial load coefficient	Bending moment coefficient	Fire resistance time of eccentrically loaded RC columns	
						Actual values	Predicted values (ANFIS)
b	d	a	μ	η	β	t	t
30.00	30.00	2.00	1.00	0.10	0.2	5.88	5.53
30.00	30.00	2.00	1.00	0.30	0.3	2.14	1.87
30.00	30.00	3.00	1.00	0.10	0.5	2.94	3.44
30.00	30.00	3.00	1.00	0.40	0.4	1.32	1.32
30.00	30.00	4.00	1.00	0.40	0.1	2.08	1.83
40.00	40.00	2.00	1.00	0.10	0.2	7.76	7.98
40.00	40.00	2.00	1.00	0.40	0	3.82	3.83
40.00	40.00	3.00	1.00	0.20	0.4	3.56	3.74
40.00	40.00	3.00	1.00	0.30	0.5	2.16	2.28
40.00	40.00	3.00	1.00	0.40	0	3.8	3.77
40.00	40.00	4.00	1.00	0.10	0.1	10.14	9.9
40.00	40.00	4.00	1.00	0.30	0.3	3.44	3.61
40.00	40.00	3.00	0.60	0.20	0.2	5.56	5.52
40.00	40.00	3.00	1.50	0.10	0	12	11.7
40.00	40.00	3.00	1.50	0.50	0.4	1.38	1.28
50.00	50.00	2.00	1.00	0.10	0.3	9.83	10.1
50.00	50.00	3.00	1.00	0.10	0.5	5.28	5.59
50.00	50.00	4.00	1.00	0.30	0.4	3.84	3.61
50.00	50.00	2.00	0.60	0.20	0.1	9.5	9.03
50.00	50.00	2.00	0.60	0.50	0	3.18	3.37
50.00	50.00	4.00	0.60	0.30	0.2	5.7	5.53
50.00	50.00	4.00	0.60	0.50	0	3.52	3.53
50.00	50.00	4.00	0.60	0.50	0.1	3.14	3.13
50.00	50.00	4.00	0.60	0.50	0.2	2.8	2.81
50.00	50.00	4.00	0.60	0.50	0.3	2.32	2.52
50.00	50.00	4.00	0.60	0.50	0.4	1.88	2.2
50.00	50.00	4.00	0.60	0.50	0.5	1.48	1.86

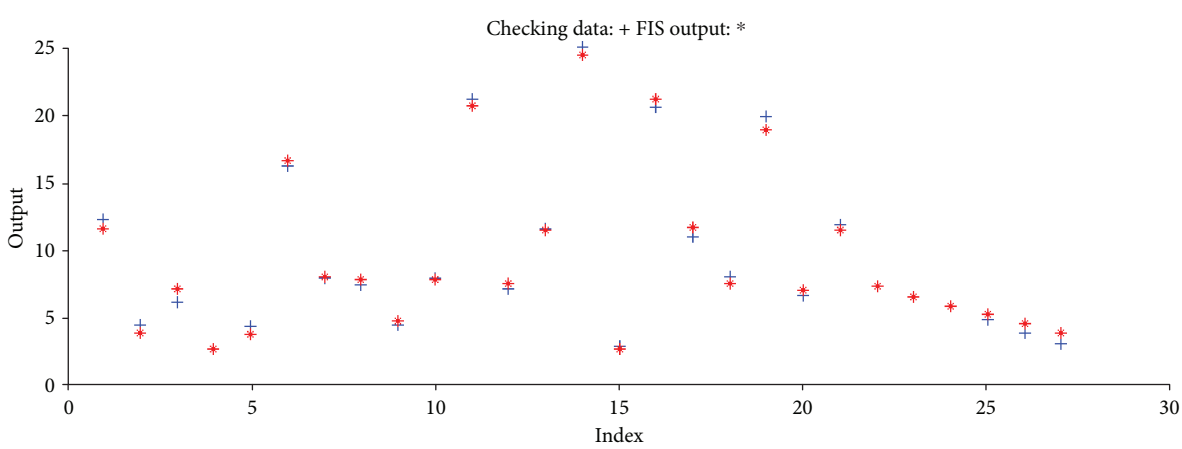

Figure 10: Comparison of actual and predicted values of fire resistance time of RC columns obtained using the ANFIS checking data.

structural elements has a huge significance in the modernization of the construction design processes. Most of the experimental models for the determination of fire resistance are extremely expensive, and analytical models are quite complicated and time-consuming. That is why a modern type of analyses, such as modeling through fuzzy neural networks, can help, especially in those cases where some prior analyses were already made.

This paper presents some of the positive aspects of their application for the determination the fire resistance of eccentrically loaded RC columns exposed to standard fire from one side. The influence of the cross-sectional dimensions, thickness of the protective concrete layer, percentage of reinforcement, and the intensity of the applied loads to the fire resistance of eccentrically loaded RC columns were analyzed using the program FIRE. The results of the performed numerical analyses were used as input parameters for training of the ANFIS model. The obtained outputs demonstrate that the ANFIS model is capable of predicting the fire resistance of the analyzed RC columns.

The results from this research are proof of the successful application of fuzzy neural networks for easily and simply solving actual complex problems in the field of construction. The obtained results, as well as the aforementioned concluding considerations, emphasize the efficiency and practicality of applying this innovative technique for the development of management models, decision making, and assessment of problems encountered during the planning and implementation of construction projects/works.

A fundamental approach based on the application of fuzzy neural networks enables advanced and successful modeling of fire resistance of reinforced concrete columns embedded in the fire compartment wall, exposed to fire on one side, thus overcoming defects typical for traditional methods of mathematical modeling.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] EN1994–1-2, *Eurocode 4 – Design of Composite Steel and Concrete Structures, Part 1-2: General Rules - Structural Fire Design*, European Committee for Standardization, Management Centre, 2005.

[2] A. Abraham and B. Nath, "A neuro-fuzzy approach for modelling electricity demand in Victoria," *Applied Soft Computing*, vol. 1, no. 2, pp. 127–138, 2001.

[3] A. Abrahim, "Neuro fuzzy systems: state-of-the-art modeling techniques," in *Connectionist Models of Neurons, Learning Processes and Artificial Intelligence*, Lecture notes in Computer sciences, J. Mira and A. Prieto, Eds., pp. 269–276, Springer-Verlag, Germany, 2001.

[4] H. Adeli and X. Jiang, "Neuro-fuzzy logic model for freeway work zone capacity estimation," *Journal of Transportation Engineering*, vol. 129, no. 5, pp. 484–493, 2003.

[5] A. Abraham, *It Is Time to Fuzzify Neural Networks! (Tutorial)*, International Conference on Intelligent Multimedia and Distance Education, Fargo, USA, 2001.

[6] D. Fuller, *Neural Fuzzy Systems*, Abo Akademi University, 1995.

[7] M. F. Azeem, Ed., *Fuzzy Inference System-Theory and Applications*, InTechOpen, 2012.

[8] N. K. Kasabov, "Foundations of neural networks, fuzzy systems and knowledge engineering," in *A Bradford Book*, The MIT Press, Cambridge, London, England, 1998.

[9] A. Abrahim and M. R. Khan, "Neuro-fuzzy paradigms for intelligent energy management," in *Connectionist Models of Neurons, Learning Processes and Artificial Intelligence*, Lecture notes in Computer sciences, J. Mira and A. Prieto, Eds., Springer-Verlag Berlin Heidelberg, 2004.

[10] A. H. Boussabaine and T. M. S. Elhag, *A Neurofuzzy Model for Predicting Cost and Duration of Construction Projects*, Royal Institution of Chartered Surveyors, 1997.

[11] S. S. H. Yasrebi and M. Emami, "Application of artificial neural networks (ANNs) in prediction and interpretation of Pressuremeter test results," in *The 12th International Conference of International Association for Computer Methods and Advances in Geomechanics (IACMAG)*, pp. 1634–1638, India, 2008.

[12] K. C. Lam, T. Hu, S. Thomas Ng, M. Skitmore, and S. O. Cheung, "A fuzzy neural network approach for contractor prequalification," *Construction Management and Economics*, vol. 19, no. 2, pp. 175–188, 2001.

[13] C. H. Ko and M. Y. Cheng, "Hybrid use of AI techniques in developing construction management tools," *Automation in Construction*, vol. 12, no. 3, pp. 271–281, 2003.

[14] J. Jassbi and S. Khanmohammadi, *Organizational Risk Assessment Using Adaptive Neuro-Fuzzy Inference System*, IFSA-EUSFLAT, 2009.

[15] M.-Y. Cheng, H.-C. Tsai, C.-H. Ko, and W.-T. Chang, "Evolutionary fuzzy neural inference system for decision making in geotechnical engineering," *Journal of Computing in Civil Engineering*, vol. 22, no. 4, pp. 272–280, 2008.

[16] A. Rashidi, F. Jazebi, and I. Brilakis, "Neurofuzzy genetic system for selection of construction project managers," *Journal of Construction Engineering and Management*, vol. 137, no. 1, pp. 17–29, 2011.

[17] E. Mehdi and G. Reza, "Risk assessment of construction projects using network based adaptive fuzzy system," *International Journal of Academic Research*, vol. 3, no. 1, p. 411, 2011.

[18] W. F. Feng and W. J. Zhu, "The application of SOFM fuzzy neural network in project cost estimate," *Journal of Software*, vol. 6, no. 8, pp. 1452–1459, 2011.

[19] M. R. Feylizadeh, A. Hendalianpour, and M. Bagherpour, "A fuzzy neural network to estimate at completion costs of construction projects," *International Journal of Industrial Engineering Computations*, vol. 3, no. 3, pp. 477–484, 2012.

[20] S. A. Ramu and V. T. Johnson, "Damage assessment of composite structures—a fuzzy logic integrated neural network approach," *Computers & Structures*, vol. 57, no. 3, pp. 491–502, 1995.

[21] M. Y. Liu and Y. Wei-guo, "Research on safety assessment of long-span concrete-filled steel tube arch bridge based on fuzzy-neural network," *China Journal of Highway and Transport*, vol. 4, p. 012, 2004.

[22] E. T. Foncesa, *A Neuro-Fuzzy System for Steel Beams Patch Load Prediction*, Fifth International Conference on Hybrid Intelligent Systems, 2005.

[23] B. Wang, X. Liu, and C. Luo, *Research on the Safety Assessment of Bridges Based on Fuzzy-Neural Network*, Proceedings of the Second International Symposium on Networking and Network Security, China, 2010.

[24] M. Jakubek, "Fuzzy weight neural network in the analysis of concrete specimens and R/C column buckling tests," *Computer Assisted Methods in Engineering and Science*, vol. 18, no. 4, pp. 243–254, 2017.

[25] A. Tarighat, "Fuzzy inference system as a tool for management of concrete bridges," in *Fuzzy Inference System-Theory and Applications*, M. F. Azeem, Ed., IntechOpen, 2012.

[26] M. A. Mashrei, "Neural network and adaptive neuro-fuzzy inference system applied to civil engineering problems," in *Fuzzy Inference System-Theory and Applications*, IntechOpen, 2012.

[27] A. Cüneyt Aydin, A. Tortum, and M. Yavuz, "Prediction of concrete elastic modulus using adaptive neuro-fuzzy inference system," *Civil Engineering and Environmental Systems*, vol. 23, no. 4, pp. 295–309, 2006.

[28] S. Tesfamariam and H. Najjaran, "Adaptive network–fuzzy inferencing to estimate concrete strength using mix design," *Journal of Materials in Civil Engineering*, vol. 19, no. 7, pp. 550–560, 2007.

[29] E. Özgan, İ. Korkmaz, and M. Emiroğlu, "Adaptive neuro-fuzzy inference approach for prediction the stiffness modulus on asphalt concrete," *Advances in Engineering Software*, vol. 45, no. 1, pp. 100–104, 2012.

[30] M. J. Chae and D. M. Abraham, "Neuro-fuzzy approaches for sanitary sewer pipeline condition assessment," *Journal of Computing in Civil Engineering*, vol. 15, no. 1, pp. 4–14, 2001.

[31] P. C. Nayak, K. P. Sudheer, D. M. Rangan, and K. S. Ramasastri, "A neuro-fuzzy computing technique for modeling hydrological time series," *Journal of Hydrology*, vol. 291, no. 1-2, pp. 52–66, 2004.

[32] A. Cao and L. Tian, "Application of the adaptive fuzzy neural network to industrial water consumption prediction," *Journal of Anhui University of Technology and Science*, vol. 3, 2005.

[33] S. Y. Chen and Y. W. Li, "Water quality evaluation based on fuzzy artificial neural network," *Advances in Water Science*, vol. 16, no. 1, pp. 88–91, 2005.

[34] F.-J. Chang and Y.-T. Chang, "Adaptive neuro-fuzzy inference system for prediction of water level in reservoir," *Advances in Water Resources*, vol. 29, no. 1, pp. 1–10, 2006.

[35] D. Hamidian and S. M. Seyedpoor, "Shape optimal design of arch dams using an adaptive neuro-fuzzy inference system and improved particle swarm optimization," *Applied Mathematical Modelling*, vol. 34, no. 6, pp. 1574–1585, 2010.

[36] T. Thipparat and T. Thaseepetch, "Application of neuro-fuzzy system to evaluate sustainability in highway desigh," *International Journal of Modern Engineering Research*, vol. 2, no. 5, pp. 4153–4158, 2012.

[37] M. Cvetkovska, *Nonlinear Stress Strain Behavior of RC Elements and Plane Frame Structures Exposed to Fire, Doctoral Dissertation*, Civil Engineering Faculty in Skopje, "Sts Cyril and Methodius" University, Macedonia, 2002.

[38] M. Lazarevska, M. Knežević, M. Cvetkovska, N. Ivanišević, T. Samardzioska, and A. T. Gavriloska, "Fire-resistance prognostic model for reinforced concrete columns," *Građevinar*, vol. 64, p. 7, 2012.

[39] http://www.mathworks.com/products/fuzzy-logic/.

[40] J.-S. R. Jang, "ANFIS: adaptive-network-based fuzzy inference system," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 3, pp. 665–685, 1993.

[41] J. Guan, J. Zurada, and S. Levitian, "An adaptive neuro-fuzzy inference system based approach to real estate property assessment," *Journal of Real Estate Research*, vol. 30, no. 4, pp. 395–421, 2008.

[42] H. Adeli, "Neural networks in civil engineering: 1989–2000," *Computer-Aided Civil and Infrastructure Engineering*, vol. 16, no. 2, pp. 126–142, 2001.

[43] E. B. Baum and D. Haussler, "What size net gives valid generalization?," *Neural Computation*, vol. 1, no. 1, pp. 151–160, 1989.

[44] M. Neshat, A. Adela, A. Masoumi, and M. Sargolzae, "A comparative study on ANFIS and fuzzy expert system models for concrete mix design," *International Journal of Computer Science Issues*, vol. 8, no. 2, pp. 196–210, 2011.

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Research Article

Urban Road Infrastructure Maintenance Planning with Application of Neural Networks

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The maintenance planning within the urban road infrastructure management is a complex problem from both the management and technoeconomic aspects. The focus of this research is on decision-making processes related to the planning phase during management of urban road infrastructure projects. The goal of this research is to design and develop an ANN model in order to achieve a successful prediction of road deterioration as a tool for maintenance planning activities. Such a model is part of the proposed decision support concept for urban road infrastructure management and a decision support tool in planning activities. The input data were obtained from Circly 6.0 Pavement Design Software and used to determine the stress values (560 testing combinations). It was found that it is possible and desirable to apply such a model in the decision support concept in order to improve urban road infrastructure maintenance planning processes.

1. Introduction

The development of urban road infrastructure systems is an integral part of modern city expansion processes. Internationally, roads are dominant transport assets and a valuable infrastructure used on a daily basis by millions of commuters, comprising millions of kilometers across the world. According to [1], the average length of public roads in OECD countries is more than 500,000 km and is often the single largest publicly owned national asset. Such infrastructure covers 15–20% of the whole city area and in city centers over 40% of the area [2]. Therefore, the road infrastructure is unarguably seen as significant and valuable public asset which should be carefully managed during its life cycle.

In general, the importance of road maintenance can be seen as the following [1]:

(i) Roads are key national assets which underpin economic activity.

(ii) Road transport is a foundation for economic activity.

(iii) Ageing infrastructure requires increased road maintenance.

(iv) Traffic volumes continue to grow and drive increased need for maintenance.

(v) Impacts of road maintenance are diverse and must be understood.

(vi) Investing in maintenance at the right time saves significant future costs.

(vii) Maintenance investment must be properly managed.

(viii) Road infrastructure planning is imperative for road maintenance for future generations.

In urban areas, the quality of road infrastructure directly influences the citizens' quality of life [3], such as the residents' health, safety, economic opportunities, and conditions for work and leisure [3, 4]. Therefore, every action needs careful planning as it is highly complex and socially sensitive. In order to deal with such problems, city governments often

encounter considerable problems during the planning phase when it is necessary to find a solution that would meet the requirements of all stakeholders and at the same time be a part of the desired development concept. As they are limited by certain annual budgeting for construction, maintenance, and remedial activities, the project's prioritization emerges as one of the most important and most difficult issues to be resolved in the public decision-making process [5].

In order to cope with such complexity, various management information systems were created. Some aimed at improving decision-making at the road infrastructure planning level in urban areas based on multicriteria methods (such as simple additive weighting (SAW) and analytic hierarchy processing (AHP)) and artificial neural networks (ANNs) [5], others on combining several multicriteria methods (such as AHP and PROMETHEE [6], AHP, ELECTRE, and PROMETHEE [7]) or just using single multicriteria method (such as AHP [8]). Deluka-Tibljaš et al. [2] reviewed various multicriteria analysis methods and their application in decision-making processes regarding transport infrastructure. They concluded that, due to complexity of the problem, application of multicriteria analysis methods in systems such as decision support system (DSS) can significantly contribute to the improvement of the quality of decision-making process regarding transport infrastructure in urban areas.

Apart from the aforementioned systems which are mainly used for strategic management, most maintenance management aspects are connected to various pavement systems. A typical pavement management system should help a decision-maker to select the best maintenance program so that the maximal use is made of available resources. Such a program answers questions such as which maintenance treatment to use and where and when to apply it. The quality of the prioritization directly influences the effectiveness of available resources, which is often the primary decision-makers' goal. Therefore, Wang et al. [9] developed an integer linear programming model in order to select a set of candidate projects from the highway network over a planning horizon of 5 years. Proposed model was tested on a small network of 10 road sections regarding two optimization objectives—maximization of the total maintenance and rehabilitation effectiveness and minimization of the total maintenance and rehabilitation disturbance cost. For years, pavement management systems have been used in highway agencies to improve the planning efforts associated with pavement preservation activities, to provide the information needed to support the pavement preservation decision process, and to compare the long-term impacts of alternative preservation strategies. As such, pavement management is an integral part of an agency's asset management efforts and an important tool for cost-effectively managing the large investment in its transportation infrastructure. Zimmerman and Peshkin [10] emphasized the issues regarding integrating pavement management and preventive maintenance with recommendations for improving pavement management systems, while Zhang et al. [11] developed a new network-level pavement asset management system utilizing life cycle analysis and optimization methods. The proposed management system allows decision-makers to preserve a healthy pavement network and minimize life cycle energy consumption, greenhouse gas emission, or cost as a single objective and also meet budget constraints and other decision-maker's constraints.

Pavements heavily influence the management costs in road networks. Operating pavements represent a challenging task involving complex decisions on the application of maintenance actions to keep them at a reasonable level of performance. The major difficulty in applying computational tools to support decision-making lies in a large number of pavement sections as a result of a long length of road networks. Therefore, Denysiuk et al. [12] proposed a two-stage multiobjective optimization of maintenance scheduling for pavements in order to obtain a computationally treatable model for large road networks. As the given framework is general, it can be extended to different types of infrastructure assets. Abo-Hashema and Sharaf [13] proposed a maintenance decision model for flexible pavements which can assist decision-makers in the planning and cost allocation of maintenance and rehabilitation processes more effectively. They develop a maintenance decision model for flexible pavements using data extracted from the long-term pavement performance DataPave3.0 software. The proposed prediction model determines maintenance and rehabilitation activities based on the density of distress repair methods and predicts future maintenance unit values with which future maintenance needs are determined.

Application of artificial neural networks in order to develop prediction models is mostly connected to road materials and modelling pavement mixtures [14–16] rather than planning processes, especially maintenance planning. Therefore, the goal of this research is to design and develop an ANN model in order to achieve a successful prediction of road deterioration as a tool for maintenance planning activities. Such a model is part of the proposed decision support concept (DSC) for urban road infrastructure management and a decision support tool in planning activities.

This paper is organized as follows: Section 2 provides a research background of the decision support concept as well as the methodology for the development of ANN prediction models as a tool for supporting decisions in DSC. In Section 3, the results of the proposed model are shown and discussed. Finally, the conclusion and recommendations are presented in Section 4.

2. Methodology

2.1. Research Background. Depending on the need of the business, different kinds of information systems are developed for different purposes. Many authors have studied possibilities for generating decision support tools for urban management in the form of various decision support systems. Such an approach was done by Bielli [17] in order to achieve maximum efficiency and productivity for the entire urban traffic system, while Quintero et al. [18] described an improved version of such a system named IDSS (intelligent decision support system) as it coordinates management of several urban infrastructure systems at the same time. Jajac et al. [5, 6] presented how different decision support models

can be generated and used at different decision-making levels for the purpose of cost-and-benefit analyses of potential infrastructure investments. A decision support concept (DSC) aimed at improving urban road infrastructure planning based on multicriteria methods and artificial neural networks proposed by Jajac et al. [4] showed how urban road infrastructure planning can be improved. It showed how decision-making processes during the planning stages can be supported at all decision-making levels by proper interaction between DSC modules.

A structure of the proposed decision support concept for urban road infrastructure management (Figure 1) is based on the author's previous research, where the "three decision levels" concept for urban infrastructure [5, 6, 19] and spatial [4, 20] management is proposed. The proposed concept is modular and based on DSS basic structure [21]: (i) database, (ii) model base, and (iii) dialog module. Interactions between modules are realized throughout the decision-making process at all management levels as they serve as meeting points of adequate models from the model base and data from the database module. Also, interactions between decision-makers, experts, and stakeholders are of crucial importance as they deal with various types of problems (from structured to unstructured).

The first management level supports decision-makers at the lowest operational management level. Besides its general function of supporting decision-making processes at the operational level, it is a meeting point of data and information where the problems are well defined and structured. Additionally, it provides information flows towards higher decision levels (arrow 1 in Figure 1). The decision-makers at the second management level (i.e., tactical management level) deal with less-defined and semistructured problems. At this level, tactical decisions are delivered, and it is a place where information basis and solutions are created. Based on applied models from the model base, it gives alternatives and a basis for future decisions on the strategic management level (arrow 2 in Figure 1), which deals with even less-defined and unstructured problems. Depending on the decision problem, various methods could be used (ANN, e.g.,). At the third management level, based on the expert deliverables from the tactical level, a future development of the system is carried out. Strategies are formed, and they serve as frameworks for lower decision and management levels (arrows 3 and 4 in Figure 1).

As the decisions made throughout the system are based on knowledge generated at the operational decision-making level, it is structured in an adequate knowledge-based system of the database (geographic information system (GIS), e.g.,). Besides DSS structure elements, which obviously influence the system at all management levels, other factors from the environment have a considerable influence on both the decision-making process as well as management processes, as is shown in Figure 1. Such structure is found to be adequate for various urban management systems, and its structure easily supports all phases of the decision-making process. Since this research is focused on the urban road infrastructure management, and particularly on the improvement of its planning process, the concept is used to support

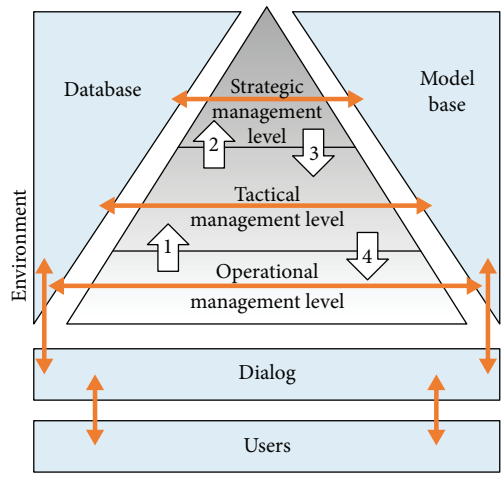

Figure 1: Structure of the decision support concept for urban road infrastructure management.

decision-making processes in the realization of these management functions. In this paper, the focus is on the maintenance planning process of the urban road infrastructure with the application of neural networks.

The development of the ANN prediction model requires a number of technologies and areas of expertise. It is necessary to collect an adequate set of data (from monitoring and/or collection of existing historical data) from the urban area. From such a collection, the data analysis is made, which serves as a starting point on the prediction model development. Importing such a prediction model into an existing or the development of a new decision support system results in a supporting tool for decision-makers, that is, public authorities in choosing the appropriate maintenance measures on time.

2.2. Development of an ANN Prediction Model. Today, the implementation of artificial neural networks in order to develop prediction models becomes a very interesting research field which could be used to solve various problems. Therefore, the idea was to develop such an ANN prediction model which would assist decision-makers in dealing with maintenance planning problems of urban road infrastructure.

In pavement construction, according to Croatian national standards for asphalt pavement design (HRN U.C4.012), one should take into consideration several layers of materials: asphalt materials, grain materials stabilized by hydraulic binder, unbound grained materials, and subgrade. Methods for pavement design are divided into two groups: empirical and analytical methods. While pavement design empirical methods are used as systematic observations on pavement performance on existing road sections, in analytical pavement, design mathematical models for calculation are included for determining strain and stresses in pavement layers, that is, road deterioration prediction. Therefore, the calculated values of stresses and strains are used for estimating pavement life and damage evaluation [22]. According to Babić [23], in order to achieve the desired durability of

pavement construction over time, it is necessary to achieve the following:

(i) The maximum vertical compressive strain on the top of subgrade does not exceed certain amount.

(ii) The horizontal radial stress (strain) at the bottom of the cement-bearing layer is less than the allowable stress (strain).

(iii) The horizontal radial stress (strain) at the bottom of the asphalt layer is less than the allowable stress (strain).

It is considered that fulfilling the above-stated requirements protects pavements from premature crack condition. Figure 2 shows the used pavement cross section for the modelling process. It is apparent that the observed construction consists of three layers, that is, asphalt layer, unbound granular material layer, and subgrade layer. Selected pavement structure is under standard load expressed in passages of ESAL (equivalent single axle load) of 80 kN, that is, axle loading by 2 wheels on each side with the axle space between them of 35 cm and the axle width of 1.8 m. Such road structure is most often used in roads for medium and low traffic loads in the Republic of Croatia.

For modelling purposes of development of an ANN prediction model, only the horizontal radial stress is observed at the bottom of the asphalt layer, under the wheel. In order to determine the stress values at the bottom of the asphalt layer analytically, the Circly 6.0 Pavement Design Software (further Circly 6.0) is used. This software was developed in Australia several decades ago, and since 1987, it has been an integral part of the Austroads Pavement Design Guide, the standard for road design in Australia and New Zealand as well as a road design worldwide. The Circly 6.0 is a software package where the rigorous flexible pavement design methodology concerning both pavement material properties and performance models is implemented (https://pavementscience.com.au/softover/circly/circly6_overview/). Material properties (Young's modulus E and Poisson's ratio), loads, and thicknesses of each layer are used as input data, while the output data is the stress value at the bottom of the asphalt layer.

In the second part of the research, a diagram (Figure 3) is presented of the performed tests, data collection for the modelling process (1), the division of the total data (2), determination of the ANN model architecture (3), testing of the adopted ANN model (4), analysis of the prediction performance of an adopted ANN model on independent dataset (5), and application of the adopted ANN model on different types of construction (6).

The ANN model is used for the purpose of achieving a successful prediction of horizontal radial stress at the bottom of the asphalt layer. The main objective is to produce the ANN prediction model based on collected data, to test it on an independent dataset, subsequently, to test the base model on an extended (independent) dataset, and, ultimately, to analyze the model's performance on several pavement structures with variable features.

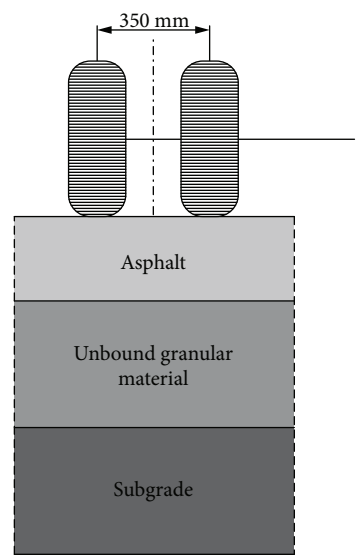

Figure 2: Cross section of the observed pavement structure.

2.2.1. Data Collection for the Modeling Process. For the needs of the ANN model production, the used input data are shown in Table 1. In total, 560 of the testing combinations are applied, containing variable values of the specific load on the pavement structure, characteristics of the asphalt layer (modulus of elasticity, thickness, Poisson's ratio, and volume binder content), unbound granular material, and subgrade (modulus of elasticity and Poisson's ratio). Circly 6.0 was used to determine the stress values (560 testing combinations) at the bottom of the asphalt layer (under the wheel). Initial activity is reduced to collecting data from the Circly 6.0 software (560 combinations) where 10 independent variables listed in Table 1 are used as input values. The dependence of dependent variables (stress) and 10 independent variables is observed. After that, the collected data are used in the process of producing and testing the ANN model.

2.2.2. Architecture Design of the ANN Model. For the purposes of this research, particularly, with the aim of taking into consideration the simultaneous impact of multiple variables on the forecasting of asphalt layer stress, the feedforward neural network was used for the ANN prediction model development. It consists of a minimum of three layers: input, hidden, and output. The number of neurons in the input and output layers is defined by a number of selected data, whereas the number of neurons in the hidden layer should be optimized to avoid overfitting the model, defined as the loss of predictive ability [24]. Since every layer consists of neurons that are connected by the activation function, the sigmoid function was used. The backpropagation algorithm was used for the training process. The configuration of the applied neural network is shown in Figure 4.

The RapidMiner Studio Version 8.0 software package is used to develop the ANN model. In order to design the architecture of the ANN model, input data (560) are collected from the Circly 6.0 Pavement Design Software. The total collected data are divided into two parts. The bigger part (70% data in the dataset) is used to design the architecture of the

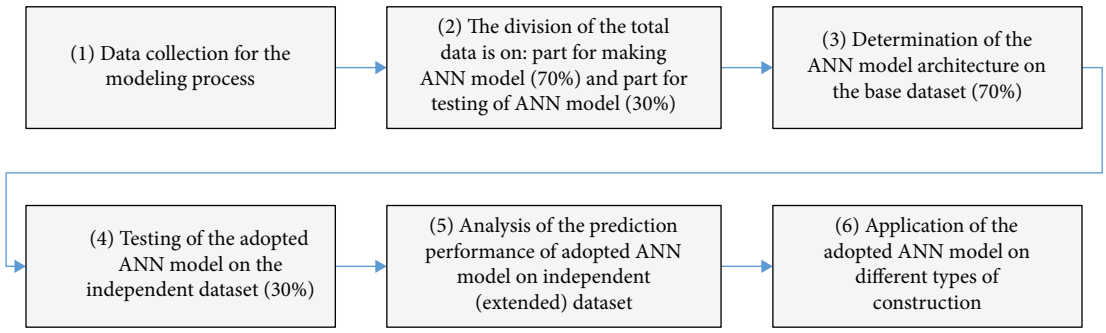

Figure 3: Diagram of the research timeline.

Table 1: Input values for the modeling process.

Independent variable number	Name of input variable	Range of used values
1	Specific load on the contact area	(0.5, 0.6, 0.7, and 0.8 MN/m^2)
2	Asphalt layer	Modulus of elasticity (2000, 4000, 6000, 8000, and 10,000 MN/m^2)
3		Thickness (3, 6, 9, 12, 15, 18, and 21 cm)
4		Poisson's ratio, $p = 0.35$
5		Volume binder content, Bc-v = 13%
6	Unbound granular material	Modulus of elasticity, Ms = 400 MN/m^2
7		Thickness, d = 20–80 cm (20, 40, 60, and 80 cm)
8		Poisson's ratio, $p = 0.35$
9	Subgrade	Modulus of elasticity, Ms = 60 MN/m^2
10		Poisson's ratio, $p = 0.45$

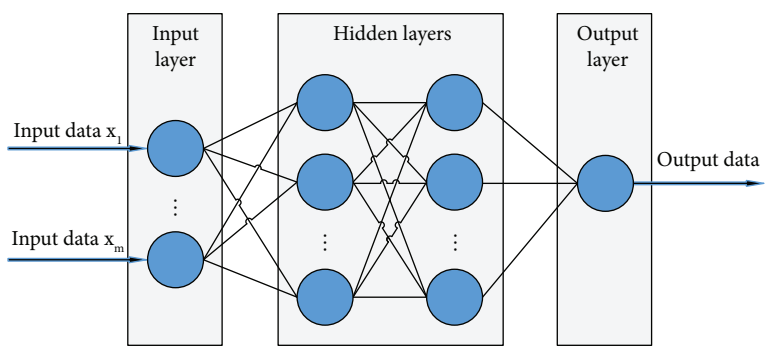

Figure 4: Configuration of the selected artificial neural network.

ANN model, while the remaining (30% of data) is used to test the accepted model. Total data are divided into those who participate in the process of developing and testing models randomly. The initial action of the pavement performance modelling process is to optimize the input parameters (momentum, learning rate, and training cycles). After the optimum (previous) parameters of the methodology are defined, the number of hidden layers and neurons in the individual layers is determined. When the design of the ANN model on the training dataset was carried out, the test of the adopted model on an independent dataset (30%) is accessed.

The optimum combination of the adopted ANN was the combination with 1 hidden layer, 20 neurons in a single layer, learning rate 0.28, and 640 training cycles. The adopted combination allowed the realization of the highest value of the coefficient of determination ($R^2 = 0.992$) between the tested and predicted values of tensile stress (for the asphalt layer).

2.2.3. Test Cases. For the purpose of this research, the input data were grouped into 3 testing cases (A, B, and C):

(i) A—base model (determining the ANN model architecture, training of the model on a set of 391 input patterns, and testing of a built-in model on the 167 independent dataset)

(ii) B—testing the A base ANN model on an independent (extended) dataset (extra 100 test data)

(iii) C—application of the developed ANN model in the process of forecasting the stresses of asphalt layers on several different road pavement structures (4 cases)

Following the analysis (Figure 5), an additional test of the base ANN model (A) on an independent (extended) dataset (B) is performed. The extended tested dataset contains an asphalt layer of thickness in the range of 2.8 to 24.1 cm, the asphalt modulus of elasticity from 1400 to 9700 MN/m^2, thickness of unbound granular material from 12 to 96 cm, and the specific load on the contact area from 0.5 to 0.8 MN/m^2. Part C shows the forecasting success of the adopted ANN model on 4 different pavement structures (independent data). Consequently, the individual relationship of asphalt layer thickness, modulus of elasticity, thickness of unbound granular layer, and specific load on the contact area versus stress is analyzed.

3. Results and Discussion

The results of the developed ANN prediction model is shown in Figure 6 in the form of the obtained values of the coefficient of determination (R^2) for the observed test cases A, B, and C. It is apparent that a very high coefficient of determination are achieved (from 0.965 (B) to 0.999 (C4)). The R^2 results are consistent with the results of Ghanizadeh and Ahadi [25] in their prediction (ANN prediction model) of the critical response of flexible pavements.

The balance of the paper presents an overview of the obtained results for cases A, B, and C, which also include a view of the testing of the basic ANN model on independent data. Figure 7 shows the linear relationship ($y = 1.0219x - 0.0378$) between the real stress values (x) and predicted stress values (y) in the case of testing the ANN model on an independent dataset (30%). From the achieved linear relationship, it is apparent that at 6 MPa, the ANN model will forecast 0.094 MPa higher stress value in comparison to the real stress values. At 1 MPa, this difference will be lower by 0.02 MPa compared to the real stress values. From the obtained linear relationship, it can be concluded that the adopted ANN model achieves a successful forecasting of stress values in comparison to the real results which were not included into the development process of the ANN model.

Figure 8 shows the linear relationship ($y = 1.0399x - 0.0358$) between the real stress values (x) and predicted stress values (y) for the case of testing the ANN model developed on an independent (extended) dataset. From the shown function relationship, it is apparent that a lower coefficient of determination of 0.965 was achieved with respect to the case A. From the obtained linear relationship, it is apparent that, at 4 MPa, the ANN model will predict 0.12 MPa higher stress value in comparison to the real stress values.

Table 2 presents the input parameters for 4 different pavement structures (C1–4) where the individual impact of the asphalt layer thickness, the asphalt elasticity modulus, the thickness of unbound granular material, and the specific load on the horizontal radial stress at the bottom of the asphalt layer (under the wheel) was analyzed. For the purposes of the analysis, additional 56 test cases were collected from the Circly 6.0 software.

In combination C1 (Figure 9), a comparison of the asphalt layer thickness and the observed stress for the road structure which in its composition has 20 and 90 cm thickness of the bearing layer was shown. As fixed values, specific load on the contact area (0.7 MPa) and modulus of elasticity—asphalt layer (4500 MPa) were used. Consequently, the relationship between the predicted stress and the real values (obtained by using the computer program) is analyzed. The obtained functional relationship clearly shows that the increasing thickness of the asphalt layer results in an expected drop in the stress of the asphalt layer. This drop in stress is greatest in unbound granular material (20 cm) where it reaches 2.44 MPa between the constructions containing 4 cm and 20 cm thick asphalt (stress loss is 0.9 MPa in construction with 90 cm thickness of the bearing layer). The largest difference between the predicted (the ANN model) and the real stress values in the amount of 0.25 MPa (unbound granular material of 20 cm, 4 cm asphalt thickness) was recorded. The average coefficient of determination (R^2) in combination to C1 amounts to the high 0.998.

Figure 10 (C2) shows the relationship between the modulus of elasticity—asphalt layer and stress in a pavement structure containing 6 and 18 cm thick asphalt layer. In the observed combination, a fixed layer thickness of 50 cm (unbound granular material) and a specific load on the contact area of 0.7 MPa are considered. As with combination C1, the relationship between predicted stress and real values is analyzed. From the obtained functional relationship, it is apparent that the growth of the modulus of elasticity—asphalt layer increases its stress as well. The increase in stress is greatest in the construction with a thinner asphalt (6 cm) where it amounts to 1.8 MPa between the constructions containing the modulus of elasticity—asphalt layer of 1400 MPa and 9700 MPa (stress growth is 0.5 MPa in construction with 18 cm thick asphalt layer). The largest difference between the predicted (from developed ANN model) and the real stress values amounts to 0.084 MPa (modulus of elasticity 4500 MPa, 6 cm asphalt thickness). The average coefficient of determination (R^2) for combination C2 amounts to high 0.996.

The following figure (Figure 11) shows the relationship between the thickness of the unbound granular layer and the asphalt layer stress with variable modulus of elasticity (1400 MPa and 9700 MPa). As a result, a fixed thickness of asphalt layer (10 cm) and the specific load on the contact area were applied (0.5 MPa). As an illustration, the relationship between the predicted and the real stress of the asphalt is shown. From the obtained results, it can be seen that with the increase of the thickness of the unbound granular layer the stress in asphalt layer is decreased. The average coefficient of determination (R^2) in combination C3 is high and amounts to 0.987. Figure 10 clearly shows a greater difference between the real and the predicted stress values on the asphalt layer (1400 MPa). The biggest difference in the stress values amounts to 0.18 MPa (40 cm thick bearing layer, 1400 MPa modulus of elasticity—asphalt layer). Larger deviations also lead to a reduction in the individual coefficient of

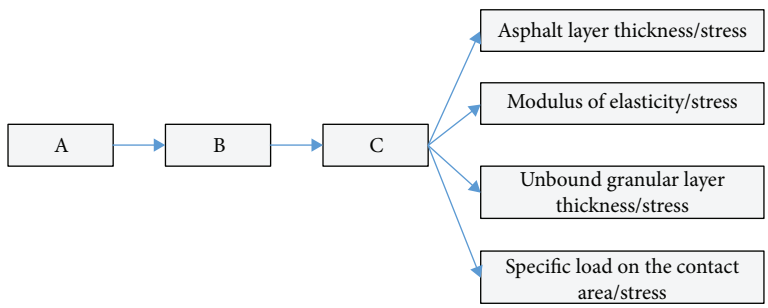

Figure 5: Test cases.

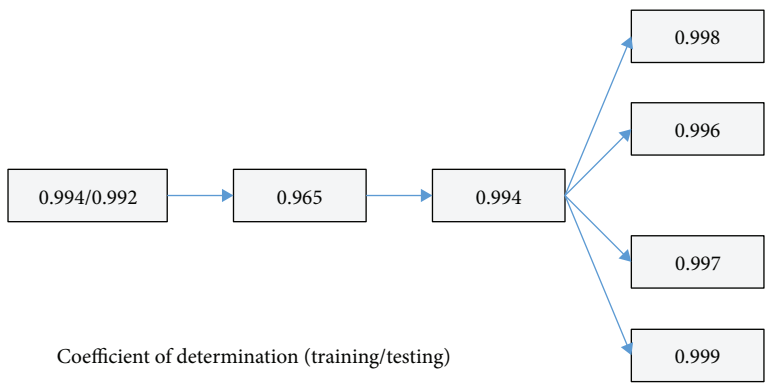

Figure 6: Test results.

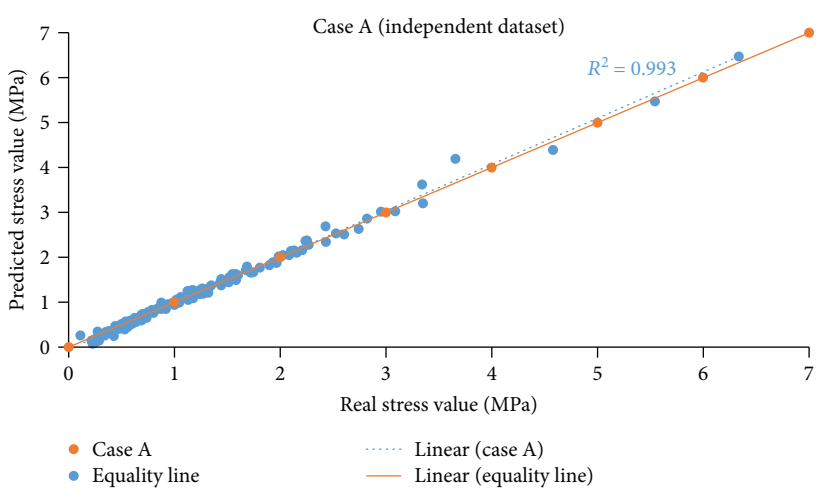

Figure 7: Results—case A.

determination to the amount of 0.958 (for asphalt layer of 1400 MPa).

The combination C4 (Figure 12) analyzes the effect of specific load on the contact area at stress values (the real and predicted values). In the observed combination, the value of the specific load on the contact area ranges from 0.5 to 0.8 MPa. It used a 40 cm thick unbound granular layer, 4 and 16 cm thick asphalt layer, and an asphalt layer modulus of elasticity in the amount of 6700 MPa. The average coefficient of determination (R^2) in this combination amounts to high 0.999. From the obtained results, it is apparent that in the case of 4 cm thick asphalt layer construction, there is an increase in the difference between the real and predicted stress values as the value of the specific load on the contact area increases. As a result, this difference is 0.13 MPa at 0.8 MPa of the specific load. It is also apparent that in the case of 16 cm thick asphalt construction, the ANN predictive model does not show any significant change in stress values due to the observed growth in the specific load on the contact area (this growth at real stress values amounts to a 0.06 MPa).

From the research project carried out, it is shown that the predicted value of stress at the bottom of the asphalt layer is

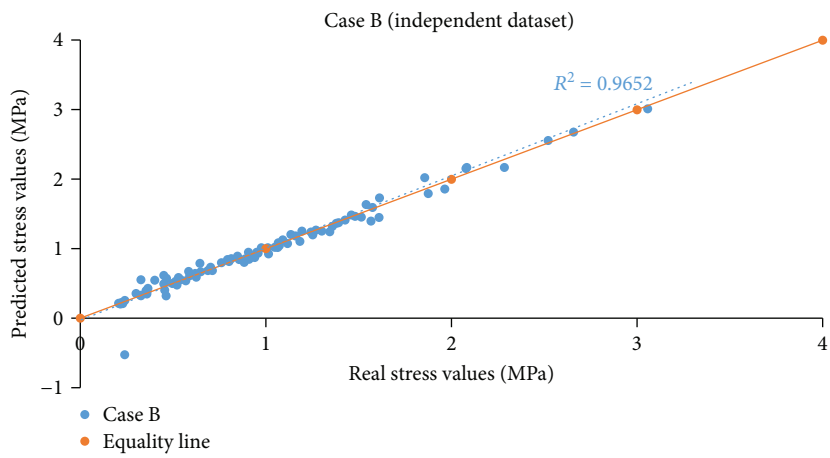

Figure 8: Results—case B.

Table 2: Input values—case C.

Case	Independent variable (x)	Dependent variable (y)	Specific load on the contact area (MPa)	Unbound granular material—thickness (cm)	Asphalt layer—thickness (cm)	Modulus of elasticity—asphalt (MPa)
C1	Asphalt layer thickness	Stress	0.7	20 and 90	4–20	4500
C2	Modulus of elasticity—asphalt	Stress	0.7	50	6 and 18	1400–9700
C3	Unbound granular material—thickness	Stress	0.5	20–100	10	1400 and 9700
C4	Specific load on the contact area	Stress	0.5–0.8	40	4 and 16	6700

Poisson's ratio, $p = 0.45$ (subgrade), $p = 0.35$ (unbound granular material), and $p = 0.35$ (asphalt layer); modulus of elasticity—unbound granular material 400 MPa; modulus of elasticity—subgrade 60 MPa.

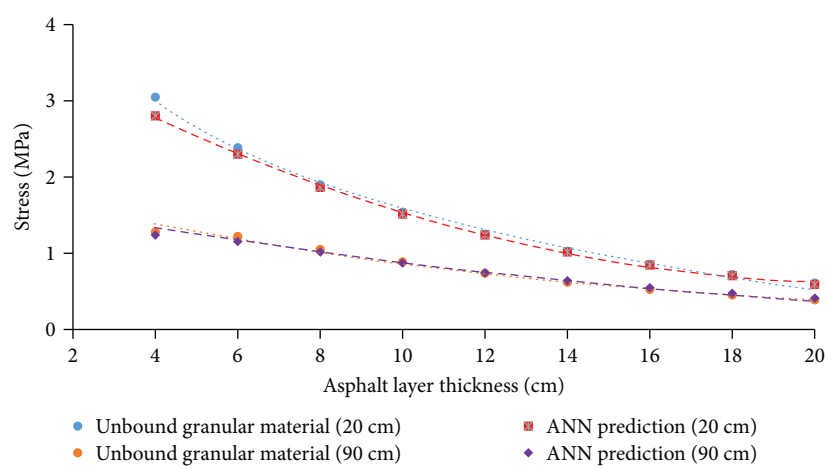

Figure 9: Results—case C1.

successfully achieved by using the developed ANN model. As previously shown, the initial testing process of the deployed ANN model was performed on an independent dataset (30% of data in the dataset), which was not used in the training phase of the observed model. Having achieved the acceptable result of the forecasting of the dependent variable, an independent (extended) set of testing cases are applied, where the previously deployed ANN model is subsequently tested. Once the trained ANN model is considered as a successful model, the same is applied in the forecasting process on the four different pavement constructions in the further course of the testing process. The obtained results confirm that it is possible to successfully use the developed ANN model in the pavement condition forecast methodology.

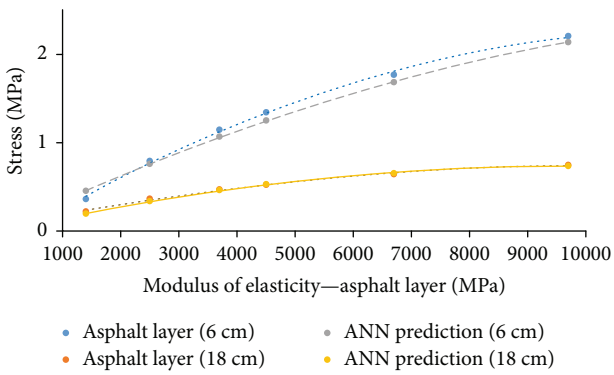

Figure 10: Results—case C2.

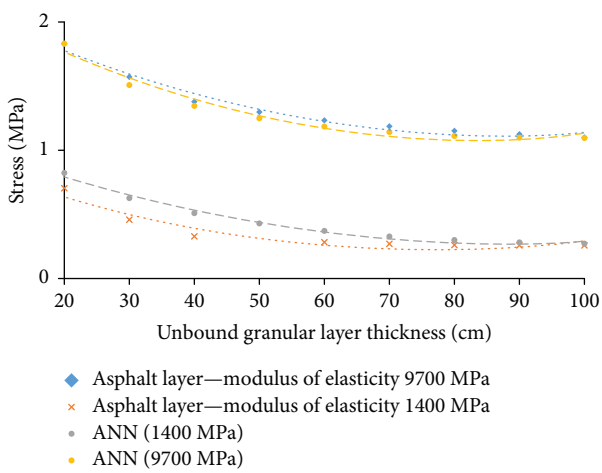

Figure 11: Results—case C3.

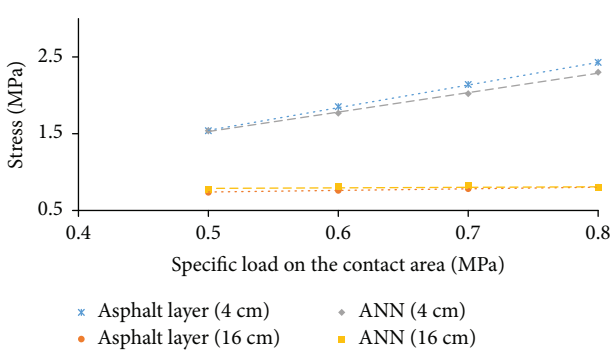

Figure 12: Results—case C4.

After the ANN modeling/testing process, it is necessary to compare the output values obtained with the permissible values. In order for the tracked construction to achieve the desired durability, it is also necessary to check that the maximum vertical compressive strain on the top of subgrade does not exceed certain amounts. As found by this research, the pavement performance forecasting success of the developed ANN model also largely depends on the range of input patterns used in the modelling process as well as on applicable independent variables.

As such, the developed ANN model gives very good prediction of real stress values at the bottom of the asphalt layers. Compared with analytical results obtained by Circly 6.0, it has very high coefficient of determination for all tested cases which are based on real possibilities of pavement structure.

As the goal of this research was to design and develop an ANN model in order to achieve a successful prediction of road deterioration as a tool for maintenance planning activities, it can be concluded that such a prediction model based on ANN is successfully developed. Therefore, such a model is part of the proposed decision support concept (DSC) for urban road infrastructure management in its model base and can be used as a decision support tool in planning activities which occur on the tactical management level.

4. Conclusions

The proposed decision support concept and developed ANN model show that complex and sensitive decision-making processes, such as the ones for urban road infrastructure maintenance planning, can correctly be supported if appropriate methods and data are properly organized and used. This paper presents an application of artificial neural networks in the prediction process of variables concerning urban road maintenance and its implementation in model base of decision support concept for urban road infrastructure management. The main goal of this research was to design and develop an ANN model in order to achieve a successful prediction of road deterioration as a tool for maintenance planning activities.

Data of the 560 different combinations was obtained from Circly 6.0 Pavement Design Software and used for training, testing, and validation purposes of the ANN model. The proposed model shows very good prediction possibilities (lowest $R^2 = 0.987$ as highest $R^2 = 0.999$) and therefore can be used as a decision support tool in planning maintenance activities and be a valuable model in the model base module of proposed decision support concept for urban road infrastructure management.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] The World Road Association (PIARC), "The importance of road maintenance, The World Road Association (PIARC)," 2014, January 2018, http://www.erf.be/images/Importance_of_road_maintenance.pdf.

[2] A. Deluka-Tibljaš, B. Karleuša, and N. Dragičević, "Review of multicriteria-analysis methods application in decision making

about transport infrastructure," *Građevinar*, vol. 65, no. 7, pp. 619–631, 2013.

[3] T. Hanak, I. Marović, and S. Pavlović, "Preliminary identification of residential environment assessment indicators for sustainable modelling of urban areas," *International Journal for Engineering Modelling*, vol. 27, no. 1-2, pp. 61–68, 2014.

[4] I. Marović, *Decision Support System in Real Estate Value Management, [Ph.D. Thesis]*, University of Zagreb, Faculty of Civil Engineering, Zagreb, Croatia, 2013.

[5] N. Jajac, I. Marović, and T. Hanak, "Decision support for management of urban transport projects," *Građevinar*, vol. 67, no. 2, pp. 131–141, 2015.

[6] N. Jajac, S. Knezić, and I. Marović, "Decision support system to urban infrastructure maintenance management," *Organization, Technology & Managament in Construction: an International Journal*, vol. 1, no. 2, pp. 72–79, 2009.

[7] B. Karleuša, A. Deluka-Tibljaš, and M. Benigar, "Possibility for implementation of multicriteria optimalisation in the traffic planning and design," *Suvremeni promet*, vol. 23, no. 1-2, pp. 104–107, 2003.

[8] D. Moazami, H. Behbahani, and R. Muniandy, "Pavement rehabilitation and maintenance prioritization of urban roads using fuzzy logic," *Expert Systems with Applications*, vol. 38, no. 10, pp. 12869–12879, 2011.

[9] F. Wang, Z. Zhang, and R. Machemehl, "Decision-making problem for managing pavement maintenance and rehabilitation projects," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1853, pp. 21–28, 2003.

[10] K. Zimmerman and D. Peshkin, "Issues in integrating pavement management and preventive maintenance," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1889, pp. 13–20, 2004.

[11] H. Zhang, G. A. Keoleian, and M. D. Lepech, "Network-level pavement asset management system integrated with life-cycle analysis and life-cycle optimization," *Journal of Infrastructure Systems*, vol. 19, no. 1, pp. 99–107, 2013.

[12] R. Denysiuk, A. V. Moreira, J. C. Matos, J. R. M. Oliveira, and A. Santos, "Two-stage multiobjective optimization of maintenance scheduling for pavements," *Journal of Infrastructure Systems*, vol. 23, no. 3, article 04017001, 2017.

[13] M. A. Abo-Hashema and E. A. Sharaf, "Development of maintenance decision model for flexible pavements," *International Journal of Pavement Engineering*, vol. 10, no. 3, pp. 173–187, 2009.

[14] N. Zavrtanik, J. Prosen, M. Tušar, and G. Turk, "The use of artificial neural networks for modeling air void content in aggregate mixture," *Automation in Construction*, vol. 63, pp. 155–161, 2016.

[15] D. Singh, M. Zaman, and S. Commuri, "Artificial neural network modeling for dynamic modulus of hot mix asphalt using aggregate shape properties," *Journal of Materials in Civil Engineering*, vol. 25, no. 1, pp. 54–62, 2013.

[16] I. Androjić and I. Marović, "Development of artificial neural network and multiple linear regression models in the prediction process of the hot mix asphalt properties," *Canadian Journal of Civil Engineering*, vol. 44, no. 12, pp. 994–1004, 2017.

[17] M. Bielli, "A DSS approach to urban traffic management," *European Journal of Operational Research*, vol. 61, no. 1-2, pp. 106–113, 1992.

[18] A. Quintero, D. Konare, and S. Pierre, "Prototyping an intelligent decision support system for improving urban infrastructures management," *European Journal of Operational Research*, vol. 162, no. 3, pp. 654–672, 2005.

[19] N. Jajac, *Design of Decision Support Systems in the Management of Infrastructure Systems of the Urban Environment, [M.S. thesis]*, University of Split, Faculty of Economics, Split, Croatia, 2007.

[20] I. Marović, I. Završki, and N. Jajac, "Ranking zones model – a multicriterial approach to the spatial management of urban areas," *Croatian Operational Research Review*, vol. 6, no. 1, pp. 91–103, 2015.

[21] E. Turban, *Decision Support and Expert Systems: Management Support Systems*, Macmillan Publishing Company, New York, NY, USA, 1993.

[22] N. Vukobratović, I. Barišić, and S. Dimter, "Influence of material characteristics on pavement design by analytical and empirical methods," *e-GFOS*, vol. 14, pp. 8–19, 2017.

[23] B. Babić, *Pavement Design*, Croatian Association of Civil Engineers, Zagreb, 1997.

[24] S. O. Haykin, *Neural Networks and Learning Machines*, Pearson Education, Upper Saddle River, NJ, USA, 2009.

[25] A. R. Ghanizadeh and M. Reza Ahadi, "Application of artificial neural networks for analysis of flexible pavements under static loading of standard axle," *International Journal of Transportation Engineering*, vol. 3, no. 1, pp. 31–42, 2016.

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Research Article

ANN Based Approach for Estimation of Construction Costs of Sports Fields

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Cost estimates are essential for the success of construction projects. Neural networks, as the tools of artificial intelligence, offer a significant potential in this field. Applying neural networks, however, requires respective studies due to the specifics of different kinds of facilities. This paper presents the proposal of an approach to the estimation of construction costs of sports fields which is based on neural networks. The general applicability of artificial neural networks in the formulated problem with cost estimation is investigated. An applicability of multilayer perceptron networks is confirmed by the results of the initial training of a set of various artificial neural networks. Moreover, one network was tailored for mapping a relationship between the total cost of construction works and the selected cost predictors which are characteristic of sports fields. Its prediction quality and accuracy were assessed positively. The research results legitimatize the proposed approach.

1. Introduction

The results presented in this paper are part of a broad research, in which the authors participate, aiming to develop tools for fast cost estimates, dedicated to the construction industry. The main aim of this paper is to present the results of the investigations on the applicability of artificial neural networks (ANNs) in the problem of estimating the total cost of construction works in the case of sports fields as specific facilities. The authors propose herein a new approach based on ANNs for estimating construction costs of sports fields.

1.1. Cost Estimation in Construction Projects. Cost estimation is a key issue in construction projects. Both underestimation and overestimation of costs may lead to a failure of a construction project. The use of different tools and techniques in the whole project life cycle should provide information about costs to the participants of the project and support a complex decision-making process. In general, cost estimating methods can be classified as follows [1, 2]:

(i) Qualitative cost estimating:

(1) Cost estimating based on heuristic methods
(2) Cost estimating based on expert judgments

(ii) Quantitative cost estimating:

(1) Cost estimating based on statistical methods
(2) Cost estimating based on parametric methods
(3) Cost estimating based on nonparametric methods
(4) Cost estimating based on analogous/comparative methods
(5) Cost estimating based on analytical methods.

The expectations of the construction industry are to shorten the time necessary to predict costs, whilst on the other hand, the estimates must be reliable and accurate enough. There are worldwide publications in which the authors report the research results which respond to these expectations. The examples of the use of a regression analysis (based on both parametric and nonparametric methods) are as follows: application of multivariate regression to predict accuracy of cost estimates on the early stage of construction projects [3], implementation of linear regression analysis methods to predict the cost of raising buildings in the UK [4], proposal and discussion of the construction cost estimation method which combines bootstrap and regression techniques [5],

and application of boosting regression trees in preliminary cost estimates for school building projects in Korea [6]. Another mathematical tool for which some examples can be given is fuzzy logic, for example, implementation of fuzzy logic for parametric cost estimation in construction building projects in Gaza Strip [7] or proposal and presentation of a fuzzy risk assessment model for estimating a cost overrun risk rating [8]. Case based reasoning (CBR) is also an approach which can be found in the publications dealing with the construction cost issue, for example, implementation of the CBR method improved by analytical hierarchy process (AHP) for the purposes of cost estimation of residential buildings in Korea [9] or the use of the case based reasoning in cost estimation of adapting military barracks also in Korea [10]. The examples of the publications which report and discuss the applications of artificial neural networks in the field of cost estimation and cost analyses in the construction process are presented in the next subsection.

1.2. Artificial Neural Networks Cost Estimation in Construction Projects. Artificial neural networks (ANNs) can be defined as mathematical structures and their implementations (both hardware and software), whose mode of action is based on and inspired by nervous systems observed in nature. In other words, ANNs are tools of artificial intelligence which have the ability to model data relationships with no need to assume a priori the equations or formulas which bind the variables. The networks come in wide variety depending on their structures, way of processing signals, and applications. The theory in this subject is widely presented in the literature (e.g., [11–15]). Main applications of ANN can be mentioned as follows (cf., e.g., [11, 12, 15]): prediction, approximation, control, association, classification and pattern recognition, associating data, data analysis, signal filtering, and optimization. ANNs features which make them beneficial in cost estimating problems (in particular for cost estimating in construction) are as follows:

(i) Applicability in regression problems where the relationships between the dependent and many independent variables are difficult to investigate

(ii) Ability to gain knowledge in the automated training process

(iii) Ability to build and store the knowledge on the basis of the collected training patterns (real-life examples)

(iv) Ability of knowledge generalization; predictions can be made for the data which have not been presented to the ANNs during a training process.

Some examples of ANN applications reported for a range of cost estimating and cost analyses in construction are replication of past cost trends in highway construction and estimation of future costs trends in this field in the state of Louisiana, USA [16], computation of the whole life cost of construction with the use of the concept of cost significant items in Australia [17], prediction of the total structural cost of construction projects in the Philippines [18], estimation of site overhead costs in the dam project in Egypt [19], prediction of the cost of a road project completion on the basis of bidding data in New Jersey, USA [20], and cost estimation of building structural systems in Turkey [21]. The authors of this paper also have their contribution in studies on the use of ANN in cost estimation problems in construction. In some previous works, the authors presented the ANN applications for conceptual cost estimation of residential buildings in Poland [22–24] and estimation of overhead cost in construction projects in Poland [25, 26].

1.3. Justification for Research. It needs to be emphasized that, despite a number of publications reporting research projects on the use of artificial neural networks in cost analyses and cost estimation in construction, each of the problems is specific and unique. Each of such problems requires an individual approach and investigation due to distinct conditions, determinants, and factors that influence the costs of construction projects. An individual approach to cost estimation in construction is primarily due to specificity of the facilities, including sports fields. The costs of a sport field are significant not only for the construction stage but also later in terms of its maintenance. The decisions made about the size, functionality, and quality are crucial for the future use and operational management of sport fields. The success in investigation of ANNs applicability in the problem will allow proposing a new approach for estimation of the construction cost of sport fields. The new approach, based on the advantages offered by neural networks, will allow predicting the total construction cost of sport fields much faster than with traditional methods; moreover, it will give the possibility of checking many variants and their influence on the cost in a very short time.

2. Formulation of the Problem and Research Framework

2.1. General Assumptions. The general aim of the research was to develop a model that supports the process of estimating construction costs of sports fields. The authors decided to investigate implementation of ANNs for the purpose of mapping multidimensional space of cost predictors into a one-dimensional space of construction costs. In a formal notation, the problem can be defined generally as follows:

$$f : X \longrightarrow Y, \tag{1}$$

where f is sought-for function of several variables, X is input of the function f, which consists of vectors $x = [x_1, x_2, \ldots, x_n]$, where variables $x_1, x_2, \ldots, x_n$ represent cost predictors characteristic of sports fields as construction objects, and Y is a set of values which represent construction costs of sports fields.

In the statistical sense, the problem comes down to solving a regression problem and estimating of a relationship f between the cost predictors being independent variables belonging to the set X and constructions cost of a sports field being dependent variable belonging to the set Y. According to the methodology in cost estimating based on statistical methods, one can distinguish between two

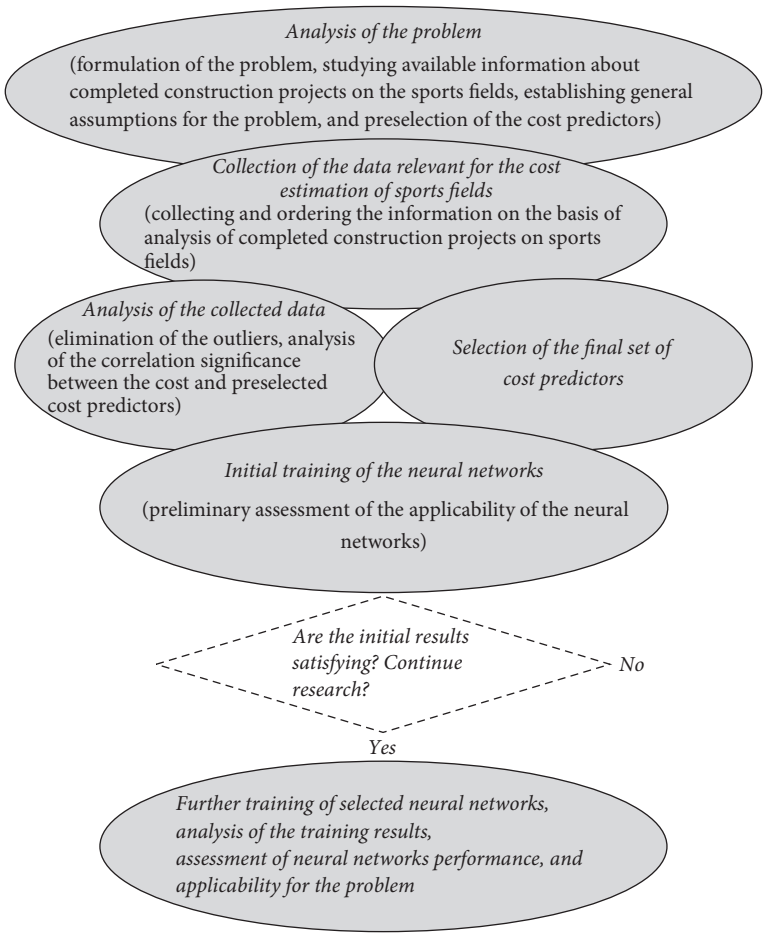

Figure 1: Scheme of the research framework (source: own study).

main approaches: estimating based on parametric methods and estimating based on nonparametric methods (cf. [1, 2, 25]). Both methods rely on the real-life data, that is, representative samples of cost predictors values and related construction costs values. In the case of the use of parametric methods function f is assumed a priori and the structural parameters of the model are estimated. On the other hand, nonparametric methods are based on fitting the function f to the data. According to the assumptions made for the research presented in this paper, the sought-for function was supposed to be implemented implicitly by ANN.

A general framework of the adopted research strategy is depicted in Figure 1.

2.2. Characteristics of Sports Fields Covered by the Research. Sports fields are facilities for which some types of works are usually repeated during the construction stage. The main types of works that can be listed are

(i) geodetic surveying,

(ii) earthworks (topsoil stripping, trenching, compacting of the natural subgrade, etc.),

(iii) works on subgrade preparation for the sports field surface,

(iv) works on sports fields surface (usually surfaces are either natural or synthetic grass),

(v) assembly of fixtures and in-ground furnishings (e.g., football/handball gates, basketball goal systems, volley ball, or tennis poles and nets),

(vi) works on fencing and ball-nets installation,

(vii) minor road works and works on sidewalks,

(viii) landscape works and arranging green areas around the sports fields.

In the course of the research, a number of completed projects on sports fields in Poland were investigated. Both the fields dedicated to one discipline and multifunctional fields were taken into account. The facilities subject to the analysis differed in size of the playing area, arranged area for communication, arranged green area, and fencing. The surfaces were of two types: either natural or synthetic grass. It must be stressed here that the quality expectations for surfaces varied significantly and played an important role in the construction costs. The completed facilities are located all over Poland both in the urban areas (in cities of different sizes) and outside the urban areas (in the villages).

Table 1: Characteristics of dependent variables and independent variables considered initially to be used in the course of a regression analysis (source: own study).

Description of the variable	Variable type	Values
Total cost of construction works	Quantitative	Cost given in thousands of PLN
Playing area of the sports field	Quantitative	Surface area measured in m^2
Location of the facility	Quantitative	Urban area (big cities, medium cities, small cities) or outside the urban area (villages)
Number of sport functions	Quantitative	Number of sports that can be played in the field
Type of the playing field surface	Categorical	Natural or artificial grass
Quality standard of the playing field's surface	Categorical	Quality standard assessed according to the available information in the tender documentation
Ball stop net's surface	Quantitative	Surface area measured in m^2
Arranged area for communication	Quantitative	Surface area measured in m^2
Fencing length	Quantitative	Length measured in m
Arranged green area	Quantitative	Surface area measured in m^2

3. Variables Analysis

3.1. Preselection of Variables. As the problem was formally expressed and the assumption about the use of ANNs was made, the authors focused on the analyses which allowed them to preselect cost predictors. The preselection was preceded by studying both technical and cost aspects of the construction projects on sports fields. This stage of the research allowed collecting the necessary background knowledge about the nature of sports fields as specific construction objects with their characteristic elements, range and sequence of construction works which must be completed, and the clients' quality expectations.

In the next step, 129 construction projects on sports fields that were completed in Poland in recent years were investigated. For the purposes of fast cost analysis, the authors preselected the following data to be the variables of the sought-for relationship:

(i) Total cost of construction works as a dependent variable

(ii) Playing area of a sports field, location of a facility, number of sport functions, the type of the playing field's surface (natural or artificial), quality standard of the playing field's surface, ball stop net's surface, arranged area for communication, fencing's length, and arranged greenery area as independent variables.

The criteria for such preselection were the availability of the data in the investigated tender documents and ensuring enough simplicity of the developed model due to which the potential client would be able to formulate the expectations about the sport field to be ordered by specifying values for potential cost predictors in the early stage of the project.

Most of the mentioned variables were of a quantitative type. In the case of the location of the facility, type of the playing field's surface, and quality standard of the playing field's surface, only descriptive information was available; the three variables were of the categorical type. Table 1 presents synthetically the characteristics of all of the variables that were preselected in the course of the analysis of the problem.

The next step included data collection and scaling categorical variables. In the case of three of the variables (namely, location of the facility, type of the playing field surface, and quality standard of the playing field's surface), categorical values were replaced by numerical values. The studies of the problem, analyses of the number of completed construction projects on sports fields, and, especially, the analyses of construction works costs brought the conclusions of how the categorical values of the three variables are associated with the costs of construction works. Table 2 explains how the change of the categorical values stimulates the costs of construction works in general. The observation made it possible to order the values and transform them into numbers in the range from 0.1 to 0.9.

Categorical values for location of the facility have taken numerical values as follows: urban area: 0.9 for big cities (population over 100,000), 0.66 for medium cities (population between 20,000 and 100,000), and 0.33 for small cities (population below 20,000); outside the urban area: 0.1 for villages. In the case of the type of the playing field, surface artificial grass has taken the value of 0.9 and natural grass has taken the value of 0.1. Finally, depending on the client's expectations and specifications available in the tender documents, the descriptions of the demands for quality standard of the playing field's surface took values from the range between 0.1 and 0.9.

The studies of tender documents for public construction projects where completion of sports fields was the subject matter of the contract allowed for collecting the data for 129 projects. The data were collected for projects completed in the last four years all over Poland. The collected information was ordered in the database. After the analysis of outliers, the authors decided to reject some extreme cases for which the total construction cost was unusually high or unusually

Table 2: General relationship between the three categorical variables and cost (source: own study).

Location of a facility	Type of the playing field surface	Quality standard of the playing field's surface	Cost
Urban area, big cities	Artificial grass	High demands	Higher
Urban area, medium cities		Moderate demands	
Urban area, small cities	Natural grass		Lower
Outside the urban area, villages		Low demands	

Table 3: Significance of correlations between the variables (source: own study).

Preselected cost predictors	Is the correlation between the dependent variable, total cost of construction works, and independent variable significant for $p$value < 0.05?	Variable's symbol (for accepted variables only)
Playing area of the sports field	Yes	x_1
Location of the sports ground	No	-
Number of sport functions	No	-
Type of the playing field surface	Yes	x_2
Quality standard of the playing field's surface	Yes	x_3
Ball stop net's surface	Yes	x_4
Arranged area for communication	Yes	x_5
Fencing length	Yes	x_6
Arranged greenery area	Yes	x_7

low. After the elimination of outliers, the data for 115 projects remained.

3.2. Selection of the Final Set of Variables. Further analysis included the investigation of the significance of correlations between the dependent variable and all of the initially considered independent variables, preselected cost predictors. The significance of correlations for p-value < 0.05 was assessed. The results of this step are synthetically presented in Table 3.

As the correlations for the two of preselected cost predictors (namely, location of the sports ground and the number of sport functions) appeared to be insignificant, they were rejected and no longer taken into account as the cost predictors.

Table 4 presents ten exemplary records with the specific numerical values of the dependent variable y (total cost of construction works) and independent variables x_j (cost predictors) accepted for the model.

Table 5 presents descriptive statistics for the variables accepted for the model. Average, minimum, and maximum values are presented for each of the variables as well as the standard deviation.

It is noteworthy that minimum value, namely, 0.00, for the variables x_4, x_5, x_6, and x_7 corresponds with the fact that in case of certain sports fields elements such as ball stop nets, arranged area for communication, fencing, and arranged greenery have not been included in a project's scope (cf. Table 4). Moreover, there is some regularity in Table 4 which manifests in the distribution of average values closer to minimum values than to maximum values. This is due to the fact that the number of small-sized and medium-sized sports fields in the database was relatively greater than the number of large-sized ones. This can be explained by a general rule valid for all kinds of construction. The number of small-sized and medium-sized facilities of all types, either newly built or existing, is always greater than those large-sized.

The database records (whose number equalled 115) were used as training patterns p for ANNs in the course of the research.

The values of the variables were scaled automatically before and after each of the ANN's training. This was done due to the functionalities of the ANN's software simulator used in the course of the research. The variables were scaled linearly to the range of values appropriate for activation functions employed for certain investigated ANN. The results, especially ANNs' training errors, presented further in the paper, are given as original, not scaled values.

4. Initial Training of Neural Networks

After the selection of independent variables, a formal notation of the relationship in the statistical sense can be given as follows:

$$y = f\left(x_1, x_2, x_3, x_4, x_5, x_6, x_7\right) + \varepsilon. \tag{2}$$

Consequently a prediction can be formally made:

$$\hat{y} = f\left(x_1, x_2, x_3, x_4, x_5, x_6, x_7\right), \tag{3}$$

where y is dependent variable, total cost of construction works, as observed in real life, $\hat{y}$ is predicted total cost of construction works, f is sought-for function, implicit relationship implemented by ANN, $x_1, x_2, x_3, x_4, x_5, x_6, x_7$ are independent variables, selected cost predictors as presented in Tables 3 and 4, and ε are random deviations (errors) for which $E(\varepsilon) = 0$,

Table 4: Exemplary records of the database including training patterns (source: own study).

p	y	x_1	x_2	x_3	x_4	x_5	x_6	x_7
5	565.8	968	0.9	0.6	0.0	196.8	602.5	0.0
13	1359	3292	0.9	0.5	600.0	2142.0	0.0	0.0
23	427.6	1860	0.9	0.3	1116.0	78.0	37.5	1000.0
37	489.5	1860	0.1	0.3	240.0	100.0	0.0	0.0
46	323.0	800	0.9	0.5	192.0	181.8	139.7	0.0
59	181.3	800	0.1	0.3	72.0	0.0	0.0	400.0
67	1972.3	4131	0.9	0.5	396.0	1096.0	207.1	2586.4
82	161.1	1650	0.1	0.1	300.0	0.0	0.0	0.0
94	250.0	1470	0.1	0.2	344.5	93.9	38.5	0.0
101	800.5	1104	0.9	0.8	295.9	1469.1	93.3	374.6

Table 5: Descriptive statistics for the models' variables (source: own study).

	Variable's symbol	Average value	Minimum value	Maximum value	Standard deviation
Dependent variable	y	457.56	33.30	2592.50	373.14
Independent variables	x_1	1333.79	275.00	5600.00	788.49
	x_2	0.59	0.10	0.90	0.27
	x_3	0.49	0.10	0.90	0.16
	x_4	300.26	0.00	2212.00	345.27
	x_5	193.16	0.00	2142.00	325.84
	x_6	105.24	0.00	602.50	121.13
	x_7	324.29	0.00	3000.00	603.26

The aim of this stage of the research, namely, the initial training of ANNs, was to assess their applicability to the problem in general and to take a decision whether to continue the research or not. A variety of feed forward ANNs were trained in the automatic mode. The overall number of networks equalled 200; the authors took into account 100 multilayer perceptron (MLP) networks and 100 radial basis function (RBF) networks as the types appropriate for the regression analysis and suitable for the formulated problem.

The main criteria to assess the applicability of the ANNs were the quality of predictions made by trained networks and the errors. The measure for quality of predictions was Pearson's correlation coefficient $R(y, \hat{y})$ between that in real life and that predicted by networks values of the independent variable, the total construction cost, whereas the measures of error was the root mean squared error (RMSE):

$$R(y, \hat{y}) = \frac{\operatorname{cov}(y, \hat{y})}{\sigma_y \sigma_{\hat{y}}},$$
$$RMSE = \sqrt{\frac{1}{n}\sum_p \left(y^p - \hat{y}^p\right)^2}, \tag{4}$$

where $\operatorname{cov}(y, \hat{y})$ is covariance between y and $\hat{y}$, σ_y is standard deviation for y, and $\sigma_{\hat{y}}$ is standard deviation for $\hat{y}$.

In the case of RBF networks, both the quality of predictions and errors were so dissatisfying that the authors decided to focus on the MLP networks only. The results for the MLP networks were satisfying; they are presented synthetically below in Figure 2 and in Table 5 and discussed briefly. The main assumptions for this stage were as follows:

(i) From the database of training patterns, learning (L), validating (V), and testing (T) subsets were randomly drawn 10 times.

(ii) The overall number of available training patterns was divided into the three subsets in relation: $L/V/T$ = 60%/20%/20%.

(iii) For each drawing, 10 different networks were trained.

(iv) The networks varied in the number of neurons in the hidden layer, H.

(v) Distinct activation functions, such as linear, sigmoid, hyperbolic tangent, and exponential, were applied in the neurons of a hidden and output layer.

Learning and validating, that is, L and V, subsets were used in the course of training process. The third subset, T, was used for testing purposes after completing the training process as an additional check of the generalization capabilities (cf., e.g., [11]). Number of neurons in the hidden layer, H, was assessed according to the following equation [27] and inequality [28]:

$$H \approx \sqrt{NM}, \tag{5}$$

where N is number of neurons in the input layer and M is number of neurons in the output layer.

$$\mathrm{NNP} = \mathrm{NNW} + \mathrm{NNB} < L, \tag{6}$$

where NNP is number of ANN's parameters, NNW is number of ANN's weights, NNB is number of ANN's biases, and L is cardinality of a learning subset.

Table 6: Summary of the initial training of ANNs for MLP networks (source: own study).

Subset	$R(y, \hat{y})$			RMSE	
	Average	Standard deviation	$R > 0.9$	Average	Standard deviation
L	0.901	0.240	82.1%	145.5	111.7
V	0.879	0.228	81.0%	108.8	57.8
T	0.881	0.233	80.5%	126.9	83.3

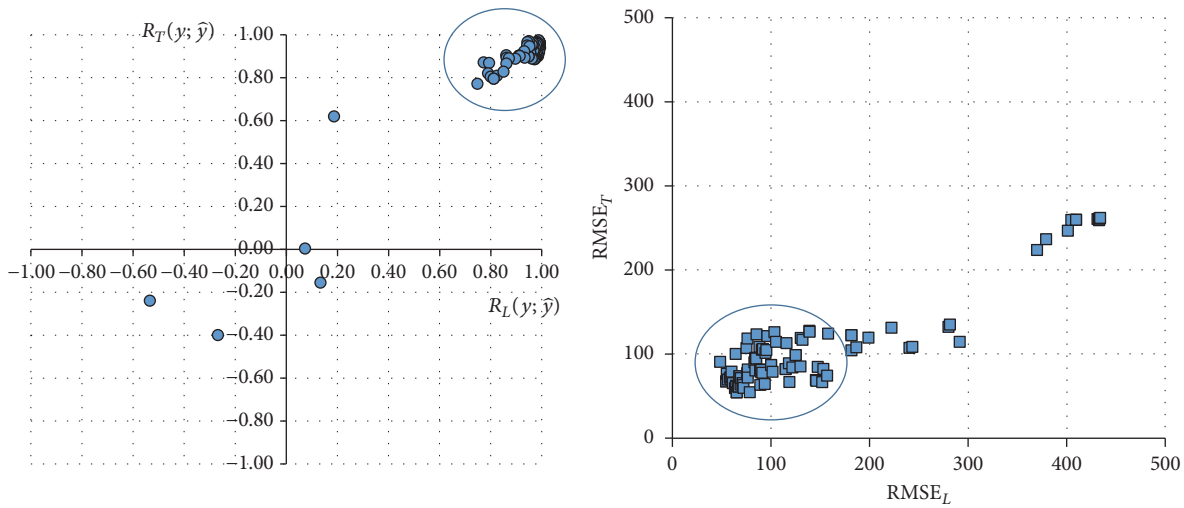

Figure 2: Quality end errors of ANNs after the initial training phase: (a) scatter diagram of Pearson's correlation coefficients and (b) scatter diagram of errors (RMSE); L and T stand for learning and testing subsets accordingly (source: own study).

From (5), $H \approx 2{,}646$. According to the assumptions about the cardinality of L subset and from inequality (6), NNP < 69. Compromising these two conditions, the number of neurons in the hidden layer, H, varied between 2 and 6.

The overall results, in terms of the quality of predictions and errors, are presented in Figures 2 and 3.

Part (a) of Figures 2 and 3 depicts scatter plots of Pearson's correlation coefficients calculated for each network after the training process. Figure 2 shows coefficients for learning and testing subsets, whereas Figure 3 shows the coefficients for learning and validating subsets. In part (b) of both figures, one can see scatter plots of errors (namely, RMSE). Figure 2 presents the scatter plot for learning and testing subsets, and Figure 3 presents the scatter plot for learning and validating subsets.

Table 6 presents the summary of the initial training of 100 MLP networks. The average and standard deviation of $R(y, \hat{y})$ as well as percentage of the cases for which $R(y, \hat{y})$ is greater than 0.9 are presented in the table. Additionally, the average and standard deviation for RMSE errors are given. All values were calculated for learning, validating, and testing subsets separately.

As can be seen both in Figures 2 and 3 and in Table 6, the correlations for most of the cases are very high. For more than 80% of networks, $R(y, \hat{y})$ was greater than 0.9 in case of learning, validating, and testing. There are evident clusters of points in Figures 2(a) and 3(a) which represent networks with the potential of the acceptable or good quality of prediction. There are only few cases outside the clusters for which the correlations coefficients are very low, due to the failure of the training process. RMSE errors are in the acceptable range at this stage.

This stage of the research confirmed the general applicability of ANNs to the investigated problem. The decision was to continue the research. Moreover, it allowed choosing a group of MLP networks to be trained in the next stage.

5. Results of Neural Networks Training in the Closing Phase of the Research

With respect to the initial training results, a group of 5 networks was chosen for the closing phase of the research. The details including networks' structures and activation functions are given in Table 7. (All of the networks consisted of 7 neurons in the input, the number of neurons ranging from 2 to 5 in one hidden layer and one neuron in the output layer. All of the networks were trained with the use of Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm.)

Assumptions for the networks training and testing were different than in the initial stage. From the set of 115 training patterns, the testing subset, T, was chosen randomly in the beginning. This subset remained unchanged for all of the networks and it was used to assess the generalization capabilities after all of the training processes. Cardinality of T subset equalled 10% of the total number of training patterns.

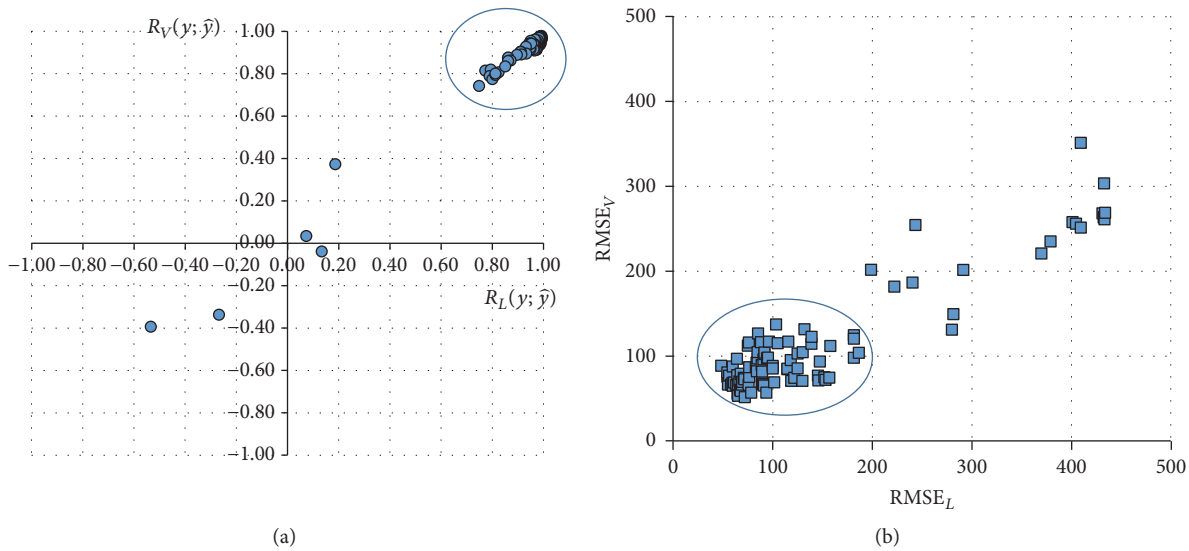

Figure 3: Quality end errors of ANNs after the initial training phase: (a) scatter diagram of Pearson's correlation coefficients and (b) scatter diagram of errors (RMSE); L and V stand for learning and validating subsets accordingly (source: own study).

Table 7: Details of the selected ANNs for further training (source: own study).

ANN	Number of neurons in the hidden layer	Activation function hidden layer	Activation function output layer	Training algorithm
$\mathrm{MLP}_{\text{e-l}}$ 7-2-1	2	Exponential	Linear	BFGS
$\mathrm{MLP}_{\text{e-ht}}$ 7-2-1	2	Exponential	Hyperbolic tangent	BFGS
$\mathrm{MLP}_{\text{e-l}}$ 7-3-1	3	Exponential	Linear	BFGS
$\mathrm{MLP}_{\text{s-l}}$ 7-5-1	5	Sigmoid	Linear	BFGS
$\mathrm{MLP}_{\text{ht-e}}$ 7-5-1	5	Hyperbolic tangent	Exponential	BFGS

The remaining patterns have been involved in the 10-fold cross-validation of the networks (cf. [11]). The patterns available for the training process after the sampling of the T subset have been divided into the 10-fold complementary learning and validating subsets. The relation of the subsets was $L/V = 90\%/10\%$ accordingly. The sum of squared errors of prediction (SSE) was used as the error function in the course of training:

$$\mathrm{SSE} = \sum_{p \in L} \left(y^p - \hat{y}^p\right)^2 . \tag{7}$$

The performance of ANNs was assessed in general in the light of correlation between real-life and predicted values, RMSE errors of the prediction (as in the stage of initial training). Table 8 presents a summary of the training results for the five chosen networks after the training process based on 10-fold cross-validation approach. The results are given in terms of the networks' performance and errors. To synthesize and assess the performance and stability of training of each network, maximum, average, and minimum as well as the dispersion of the correlation coefficients $R(y, \hat{y})$ between real-life and predicted values were calculated. Errors, namely, RMSE values, are presented in the same manner. Both correlations and errors are given separately for L, V, and T subsets. The analysis of the results made it possible to choose finally one of the five networks. The most stable performance was observed for the $\mathrm{MLP}_{\text{s-l}}$ 7-5-1.

Figure 4 depicts a scatter plot of the points that represent pairs $(y^p, \hat{y}^p)$ for the finally chosen network $\mathrm{MLP}_{\text{s-l}}$ 7-5-1. Real-life values y are set together with predicted values $\hat{y}$. The points represent training results for learning and validating subsets, as well as testing results for testing subset. In the legend of the chart, apart from the letters L, V, and T that explain membership of the certain pattern to the learning, validating, or testing subset accordingly, the numbers from 1 to 10 are given next to each letter. These numbers reveal the kth fold of the cross-validation process. In Figure 4, one can see that the points in the scatter plot are decomposed along a perfect fit line. The deviations are in the acceptable range. In respect of the analysis of $R(y, \hat{y})$, RMSE errors, and distribution of points in the scatter plot, the results are satisfactory.

Two more criteria, relating to the accuracy of cost estimation, were also specified for assessment of the selected network $\mathrm{MLP}_{\text{s-l}}$ 7-5-1. The accuracy of estimates was assessed with the use of three error measures: mean absolute percentage error (MAPE), absolute percentage error calculated for

Table 8: Results of the selected ANNs training (source: own study).

ANN	$R(y, \hat{y})$			RMSE		
	L	V	T	L	V	T
$MLP_{e\text{-}l}$ 7-2-1						
Max	0.992	0.997	0.997	92.043	111.521	68.006
Average	0.985	0.982	0.993	66.416	63.681	41.286
Min	0.973	0.948	0.985	49.572	20.138	26.656
Standard deviation	0.005	0.015	0.004	11.620	24.243	12.338
$MLP_{e\text{-}ht}$ 7-2-1						
Max	0.994	0.994	0.991	150.544	376.102	79.538
Average	0.978	0.979	0.983	73.351	90.999	57.609
Min	0.933	0.933	0.979	43.473	40.899	35.816
Standard deviation	0.022	0.018	0.003	31.521	95.430	13.082
$MLP_{e\text{-}l}$ 7-3-1						
Max	0.994	0.994	0.991	150.544	376.102	79.538
Average	0.978	0.979	0.983	73.351	90.999	57.609
Min	0.933	0.933	0.979	43.473	40.899	35.816
Standard deviation	0.022	0.018	0.003	31.521	95.430	13.082
$MLP_{s\text{-}l}$ 7-5-1						
Max	*0.997*	*0.994*	*0.996*	*65.226*	*96.700*	*71.010*
Average	*0.992*	*0.983*	*0.991*	*46.222*	*59.770*	*39.252*
Min	*0.986*	*0.949*	*0.980*	*30.333*	*29.581*	*19.582*
Standard deviation	*0.004*	*0.015*	*0.008*	*12.048*	*17.682*	*18.116*
$MLP_{ht\text{-}e}$ 7-5-1						
Max	0.996	0.995	0.996	129.738	211.452	83.939
Average	0.979	0.980	0.980	77.525	72.796	50.383
Min	0.946	0.957	0.952	32.191	41.891	27.691
Standard deviation	0.013	0.013	0.014	27.375	49.569	18.072

Table 9: MAPE and PE_{max} errors calculated for the $MLP_{s\text{-}l}$ 7-5-1 (source: own study).

$MLP_{s\text{-}l}$ 7-5-1	L	V	T
MAPE			
Max	18.76%	25.13%	21.20%
Average	12.68%	14.43%	9.97%
Min	7.49%	5.54%	5.60%
Standard deviation	3.49%	5.66%	4.44%
PE_{max}			
Max	115.83%	104.72%	93.42%
Average	65.47%	61.55%	46.67%
Min	34.34%	9.76%	11.87%
Standard deviation	21.35%	27.59%	17.65%

each pattern (PE^p), and maximum absolute percentage error (PE_{max}):

$$\begin{aligned} \mathrm{MAPE} &= \frac{100\%}{n} \sum_p \left| \frac{y^p - \hat{y}^p}{y^p} \right|, \\ \mathrm{PE}^p &= \left| \frac{y^p - \hat{y}^p}{y^p} \right| 100\%, \\ \mathrm{PE}_{\max} &= \max\left(\mathrm{PE}^p\right). \end{aligned} \tag{8}$$

Table 9 shows the maximum, average, and minimum MAPE and PE_{max} errors, as well as the standard deviations of these errors, after the 10-fold cross-validation for the selected network $MLP_{s\text{-}l}$ 7-5-1. The errors are given for the learning, validating, and testing, that is, L, V, and T, subsets, respectively.

MAPE and PE_{max} errors have been carefully investigated for the selected network in all of 10 cases of cross-validation training and testing. In respect of average MAPE errors, the results were satisfying. Average MAPE errors were expected to be smaller than 15% for learning, validating, and testing

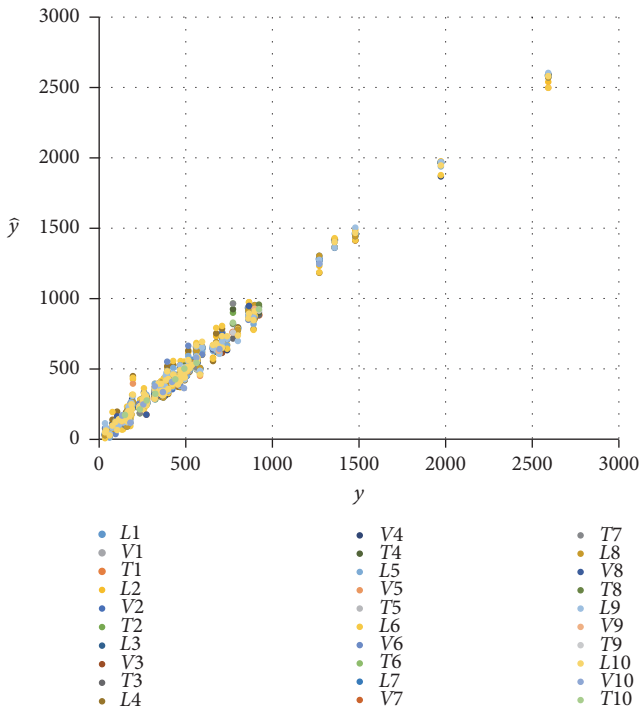

Figure 4: Scatter plot of $\hat{y}$ and y values for the selected $MLP_{s\text{-}l}$ 7-5-1 network (source: own study).

subsets. This objective was achieved. In case of PE_{max} errors, the authors expected the values lower than 30%. Table 9 reveals that the PE_{max} errors are greater than 30%. This fact has prompted the authors to examine PE^p errors. Analysis of the distribution of PE^p errors revealed that most of these errors were smaller than 30% and only few values in each of the cross-validation folds values exceeded 30%.

A thorough analysis of the selected network, namely, $MLP_{s\text{-}l}$ 7-5-1, in terms of the training results, performance, and errors allowed selecting this network to implement implicitly the sought-for relationship f. In conclusion, the selected $MLP_{s\text{-}l}$ 7-5-1 may be proposed as the tool which supports cost estimation of construction works in the projects related to sports fields.

6. Summary and Conclusion

In this paper, the authors presented their investigations on applicability of ANNs in the problem of estimating the total cost of construction works for sports fields. The research allowed the authors to confirm assumptions about the general applicability of the MLP type networks as the tool which has the potential of mapping the relationship between the total cost of construction works and selected cost predictors which are characteristic of sports fields. On the other hand, the RBF type networks appeared to not be suitable for this particular cost estimation problem.

Apart from the general conclusions about the applicability of ANNs, one type of network tailored for this problem was selected from a broad set of various MLP networks. The analysis of the results indicates a satisfactory performance of the selected network in terms of correlations between the real cost and cost predictions. The level of the MAPE and RMSE errors is acceptable. For now, the proposed approach allows the following:

(i) Estimating cost of construction works for a couple of variants of sports fields in a very short time

(ii) Supporting the decisions made by the client being aware of the range of the cost estimation accuracy.

The obtained results encourage continuation of the investigations which will aim to improve the model, especially to lower the PE_{max} errors. The authors intend to collect additional data which will enable them to exceed the number of training patterns. Moreover, the authors intend to investigate in the near future more complex tools based on ANNs, such as committees of neural networks.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

The authors use the STATISTICA software in their research; therefore some of the presented assumptions for neural networks training are made due to the functionality of the tool.

References

[1] P. M. M. Foussier, *From Product Description to Cost: A Practical Approach, : The Parametric Approach*, vol. 1, Springer Science Business Media, 2006.

[2] A. Layer, E. T. Brinke, F. Van Houten, H. Kals, and S. Haasis, "Recent and future trends in cost estimation," *International Journal of Computer Integrated Manufacturing*, vol. 15, no. 6, pp. 499–510, 2002.

[3] S. M. Trost and G. D. Oberlender, "Predicting accuracy of early cost estimates using factor analysis and multivariate regression," *Journal of Construction Engineering and Management*, vol. 129, no. 2, pp. 198–204, 2003.

[4] D. J. Lowe, M. W. Emsley, and A. Harding, "Predicting construction cost using multiple regression techniques," *Journal of Construction Engineering and Management*, vol. 132, no. 7, Article ID 002607QCO, pp. 750–758, 2006.

[5] S. Varghese and S. Kanchana, "Parametric Estimation of Construction Cost Using Combined Bootstrap And Regression Technique," in *Proceedings of the International Journal of Civil Engineering and Technology*, vol. 5, pp. 201–205, 2014.

[6] Y. Shin, "Application of boosting regression trees to preliminary cost estimation in building construction projects," *Computational Intelligence and Neuroscience*, vol. 2015, Article ID 149702, 2015.

[7] N. I. El Sawalhi, "Modelling the Parametric Construction Project Cost Estimate using Fuzzy Logic," in *Proceedings of the International Journal of Emerging Technology and Advanced Engineering*, vol. 2, pp. 63–636, 2012.

[8] I. Dikmen, M. T. Birgonul, and S. Han, "Using fuzzy risk assessment to rate cost overrun risk in international construction projects," *International Journal of Project Management*, vol. 25, no. 5, pp. 494–505, 2007.

[9] S.-H. An, G.-H. Kim, and K.-I. Kang, "A case-based reasoning cost estimating model using experience by analytic hierarchy process," *Building and Environment*, vol. 42, no. 7, pp. 2573–2579, 2007.

[10] S. H. Ji, M. Park, and H. S. Lee, "Case adaptation method of case-based reasoning for construction cost estimation in Korea," *Journal of Construction Engineering and Management*, vol. 138, no. 1, pp. 43–52, 2011.

[11] C. M. Bishop, *Neural Networks for Pattern Recognition*, Oxford University Press, New York, NY, USA, 1995.

[12] S. Haykin, *Neural networks: A Comprehensive Foundation*, Prentice Hall PTR, 1994.

[13] S. Osowski, "Sieci neuronowe w ujeciu algorytmicznym," *Wydawnictwa Naukowo-Techniczne*, 1996.

[14] S. Osowski, "Sieci neuronowe do przetwarzania informacji," *Oficyna Wydawnicza Politechniki Warszawskiej*, 2000.

[15] R. Tadeusiewicz, *Sieci neuronowe*, vol. 180, Akademicka Oficyna Wydawnicza, Warszawa, 1993.

[16] C. G. Wilmot and B. Mei, "Neural network modeling of highway construction costs," *Journal of Construction Engineering and Management*, vol. 131, no. 7, pp. 765–771, 2005.

[17] A. Alqahtani and A. Whyte, "Artificial neural networks incorporating cost significant items towards enhancing estimation for (life-cycle) costing of construction projects," *Australasian Journal of Construction Economics and Building*, vol. 13, no. 3, pp. 51–64, 2013.

[18] C. L. C. Roxas and J. M. C. Ongpeng, "An Artificial Neural Network Approach to Structural Cost Estimation of Building Projects in the Philippines," in *Proceedings of the DLSU Research Congress*, p. 1, Manila, 2014.

[19] I. Elsawy, H. Hosny, and M. A. Razek, "A neural network model for construction projects site overhead cost estimating in Egypt," *International Journal of Computer Science Issues*, vol. 8, no. 3, pp. 273–283.

[20] T. P. Williams, "Predicting completed project cost using bidding data," *Construction Management and Economics*, vol. 20, no. 3, pp. 225–235, 2002.

[21] H. M. Günaydin, S. Z. Dogan, H. M. Günaydın, and S. Z. Doğan, "A neural network approach for early cost estimation of structural systems of buildings," in *Proceedings of the International Journal of Project Management*, vol. 22, pp. 595–602, 2004.

[22] M. Juszczyk, "The Use of Artificial Neural Networks for Residential Buildings Conceptual Cost Estimation," in *Proceedings of the 11th International Conference of Numerical Analysis and Applied Mathematics 2013, ICNAAM 2013*, pp. 1302–1306, Greece, September 2013.

[23] M. Juszczyk, "Application of committees of neural networks for conceptual cost estimation of residential buildings," in *Proceedings of the International Conference on Numerical Analysis and Applied Mathematics 2014, ICNAAM 2014*, Greece, September 2014.

[24] M. Juszczyk, "The Challenges of Nonparametric Cost Estimation of Construction Works with the use of Artificial Intelligence Tools," in *Proceedings of the Creative Construction Conference, CCC 2017*, pp. 415–422, Croatia, June 2017.

[25] M. Juszczyk, A. Lesniak, and A. Leśniak, "Site overhead cost index prediction using RBF Neural Networks. Transactions on Economics and Management," *ICEM*, pp. 381–386, 2016.

[26] A. Leśniak, "The application of artificial neural networks in indirect cost estimation," in *Proceedings of the 11th International Conference of Numerical Analysis and Applied Mathematics 2013, ICNAAM 2013*, pp. 1312–1315, Greece, September 2013.

[27] E. Pabisek, Systemy hybrydowe integrujące MES i SSN w analizie wybranych problemów mechaniki konstrukcji i materiałów, Wydawnictwo Politechniki Krakowskiej, Kraków, 2008.

[28] Z. Waszczyszyn, "Zastosowanie sztucznych sieci neuronowych w inzynierii ladowej, XLI Konferencja Naukowa KILiW PAN i Komitetu Nauki PZITB," *Kraków-Krynica*, vol. tom 9, pp. 251–288, 1995.

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Research Article

Assessment of the Real Estate Market Value in the European Market by Artificial Neural Networks Application

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Using an artificial neural network, it is possible with the precision of the input data to show the dependence of the property price from variable inputs. It is meant to make a forecast that can be used for different purposes (accounting, sales, etc.), but also for the feasibility of building objects, as the sales price forecast is calculated. The aim of the research was to construct a prognostic model of the real estate market value in the EU countries depending on the impact of macroeconomic indicators. The available input data demonstrates that macroeconomic variables influence determination of real estate prices. The authors sought to obtain correct output data which show prices forecast in the real estate markets of the observed countries.

1. Introduction

The difficulty or impossibility of constructing an overall model with potential reactions and counterreactions (participants or agents) stems from the complexity of social, economic, and financial systems. It is assumed that the methodology of the neural network with evident complexity of the system, the usual incomprehensibility and general impracticality of the model, can help to emulate and encourage the observed economy or society. The problem is more obvious if one tries to control all possible variables and potential results in the system as well as to include all their dynamic interactions [1]. The application of artificial neural networks as well as econometric models is characterized by specific advantages and disadvantages. Nevertheless, neural networks have been imposed as a real alternative to econometric methods, that is, as a powerful tool for assessment and forecasting, for example, in the field of evaluating real estate. It is specially emphasized that it is possible to find estimated values instead of exact values.

Artificial neural networks are relatively new computer tools that are widely used in solving many complex real problems. Their attractiveness is a product with good characteristics in data processing, tolerance of input data errors, high learning opportunities on examples, easy adaptation to changes, and generalization of the methodology for developing successful artificial neural networks starting with conceptualization projects, through design projects, to implementation projects [2]. The use of artificial neural networks for forecasting has led to a vast increase in research over the past two decades [3].

A generation of various prognostic models is based on the use of artificial neural networks, which are recently being studied as a contemporary interdisciplinary field at many universities, which help solve many engineering problems that cannot be solved using traditional methods. Researched neural networks are used successfully as an analytical tool for relevant forecasts that greatly improve the quality of decision-making at various levels. The common problem of successful applications of artificial neural networks in forecasts and

modeling is related to the lack of necessary data—the data available is "noisy" or incomplete and the circumstances that the quantities being modeled are governed by multivariate interrelationships [4]. On the other hand, a large number of studies point to the fact that prognostic models obtained by the use of artificial neural networks exhibit a satisfactory degree of accuracy and are particularly useful in situations for preperformed numerical or experimental researches [5]. The use of these models has been explored and demonstrated reliability in a large number of applications in construction [6–11].

The wide scientific and technical use of neural networks in the conditions of increased complexity of the market, when they show superiority (effectiveness) in an unstable environment, is acceptable to analysts, investors, and economists despite the shortcomings. The multidisciplinarity of neural networks and their complexity coverage makes them suitable for assessing market variables, that is, underlying, indexed, and derivative financial instruments. Comparing the instability of forecasts obtained using neural networks with the encompassed volatility of the S&P Index futures options and applying the BAW pricing model of options to futures, Hamid concluded that forecasts from neural networks are better than the implied instability forecasts and slightly different from the realized volatility [12].

Models of artificial neural networks provide reasonable accuracy for many engineering problems that are difficult to solve by conventional engineering approaches of engineering techniques and statistical methods [13, 14]. The application of artificial neural networks in the construction sector is of great importance and usable value. Recent literature suggests that the methodology of neural networks is largely used to model different problems and phenomena in the field of construction [15–20].

Artificial neural networks are useful for modeling the relationship between inputs and outputs directly on the basis of observed data. As already noted, they are capable of learning, generalizing results, and responding to highly expressed incompleteness or incompleteness of available data [21]. As artificial neural networks have better performance than multivariate analysis because they are nonlinear, they are able to evaluate subjective information difficult to include in traditional mathematical approaches. Furthermore, the prominent abilities of neural networks are particularly evident in complex systems such as the real estate system, where in recent years artificial neural networks are widely used to create a model for estimating prices in real estate markets. A number of such models have been published in scientific and professional literature. Thus, in the last decade of the 20th century, Borst defined a number of variables for the design of a model based on artificial neural networks to appraise real estate in New York State, demonstrating that the model is able to predict the real estate price with 90% accuracy [22].

2. Materials and Methods

The problem of assessing the market value of real estate in construction has always been current from the angles of both the real estate buyers and sellers/investors and in particular for future investments. Therefore, in theory and practice, there are various methods for determining the market value of real estate. Given that the market value of a property is influenced by a large number of factors, the process of estimating the real estate market is quite complex and is always current again. A negative assessment practice that only confirms the agreed real estate price is lighter but less precise and can lead to deviations of estimated value from the real market value of real estate [23]. As part of traditional methods of estimation derive from the impact of objective factors on the real estate price, neglecting the undeniable influence of subjective factors that have a significant impact on the price of real estate, generalization of the application of these methods is not possible because the real estate market in different countries is influenced by various objective and subjective factors. The hedonistic real estate assessment method, based on a multiple regression analysis, though often used to test new estimation methods, is burdened by initial assumptions and is not sufficiently rational to evaluate [23, 24].

With the development of new computer and mathematical modeling methods, the trend of developing new approaches for real estate market assessment is notable. Namely, the use of artificial neural networks has proved to be justified in the development of unconventional methods for assessing real estate market value which enable a more objective and more accurate estimate of real estate in the market. As the valuation process is always a problem in free market economies, market participants usually do not have complete and accurate pricing information which is why they are considering a variety of factors and different relationships between them. In the real estate market, there is usually a more pronounced lack of accurate information compared to information about another commodity because data is usually not available in a consistent format. Analysis and interpretation of general trends are hampered by the sparse variety of characteristics/properties of these commodities, usually related to a particular location [25]. Therefore, a large number of authors elaborated other approaches as an alternative to the conventional method of assessment and developed new models for assessing the market value of real estate that are capable and usable for similar purposes [26–28].

Developed models of artificial neural networks have shown that residential property markets are under the influence of different economic and financial environments. The aim of developing such models is to indicate, inter alia, whether the economic and financial situation of the observed countries reflects the general economic situation on the real estate market. The results showed that the economic and financial crisis in these countries had different impacts on real estate prices [29]. The methodology based on rough set theory and on artificial neural networks proved to be suitable for the convergence of residential property prices index [29, 30]. During the last decade, the literature analyzed the impact of property price volatility on the economy in general: unemployment, consumer confidence in government, banking practices, and social costs. On the other hand, the macroeconomic situations, such as the business cycle, employment rates, income growth, interest rates, inflation rates, loan supply, returns on real estate investments, and

other factors, such as population growth, have had a significant impact on housing prices.

Contrary to the dominant application of multiple regression models, involving human estimations, the use of artificial neural networks, the model of artificial intelligence, allows the hidden nonlinear connections between the modeled variables to be uncovered. In the context of neural networks, a special place was occupied by the so-called backpropagation models. These neural networks contain series of simple interconnected neurons (or nodes) between the input and output vectors. Pi-Ying used a backpropagation neural network as a tool for constructing a housing price model for a selected city [31]. The paper investigates the importance of the application of neural network technologies in the real estate appraisal problem. Starting from the consequences of the nature of the neural network model, Pi-Ying concludes that the model creates a larger prediction error compared to multiple regression analysis. However, by estimating a large number of real estate properties, Peterson and Flanagan found that artificial neural networks, compared to linear hedonic pricing models, create significantly minor errors in dollar pricing and have greater out-of-sample precision and there is a better extrapolation in a more volatile environment [32].

According to Limsombunchai (2004), the hedonistic cost model and the artificial neural network emphasized that the hedonistic technique is generally unrealistic in dealing with the housing market in any geographic area as a single unit. Compared to neural network models, this model shows poorer results in the out-of-sample prediction [33]. Market imperfections, complemented by bid rigidity and heterogeneity of quality, contribute to the deviation of real estate prices from the fundamental value. Consequently, under sustainable deviation conditions, the problem of adverse selection is spurred, and, in the periods of financial liberalization and the boom-bust cycle, the consequence (distortion) is moral hazard [30]. The empirical and operational framework suggests that the residential property market directly determined the magnitude of the economic growth.

European economic growth is supported by the expanded ECB stimulus (quantitative easing), which has increased liquidity, confidence, and domestic consumption by creating a fundament that impacts the real estate market. Growth, that is, the boom of house prices in Europe, shows continuity lately. This can be tracked over the momentum which is increasing if the property market grows faster this year compared to the previous (or fall below). Therefore, this is a "change in change" measure which shows that most of the housing market is slowing down, although the boom continues strongly in Europe [34]. The factor that has affected the European housing market is GDP growth. In the beginning of the previous decade, the correlation between lagging in GDP growth and house prices in the EU was 81%. According to these analyzes, the expected sluggish growth of the economy should limit the growth of apartments prices in the coming years.

Interest rates, as another economic indicator of the real estate market, depend on monetary policy in the ECB and other central banks in the EU. Low interest rates are the result of expansive monetary policy which stimulates the real estate market. There is a correlation of residential lending and house prices. The rise in house prices is a consequence of the growth of residential lending, and as a result of price rises, the ratio of resident debt to household disposable income is changing. This indebtedness of households along with the household debt capacity becomes a determinant of the rise in house prices. There are two consequences of cheap residential housing in the European Union (2015): the rapid rise in property prices in certain markets and the great difference in transaction prices between cities and countries [35].

Housing is not only an important segment of household wealth but also a key sector of the real economy. The decline in housing construction can be reflected negatively (directly or indirectly) on financial stability and the real economy. In addition, the role of the loan is significant in the rise and recession of housing. Financial and macroeconomic stability are significantly affected by the development of the residential real estate sector. The main responsibility of macroprudential authorities is to analyze the vulnerabilities of this market. In the EU, European Systemic Risk Board has the mandate to implement "macroprudential oversight of the financial system within EU in order to contribute to the prevention or mitigation of systemic risk." The ESRB identifies countries in the EU that have medium-term sensitivities that can be the cause of systemic risk and result in serious negative consequences. Horizontal analysis based on key indicators, risk analysis, and analysis of structural and institutional factors (vertical) are implemented [36].

In this paper, a model for estimating real estate prices in 27 European countries has been defined. This research paper indicates the author's assumption was aided by a prognostic model using artificial neural networks with the available factors influencing the real estate price formation. These factors can obtain accurate real estate prices in the European market which can have a significant value in the decision-making process of buying real estate in the European market.

Otherwise, in literature there are various approaches to the division of factors that more or less influence the formation of prices in the real estate markets. One of the usual divisions is on macroenvironment factors (e.g., exchange rate, employment, GDP, loan interest rate, and geofactors) and microenvironment factors (mostly related to construction environment) [37]. In addition to this division, there is a division of factors into rational ones related to the real price of real estate and irrational ones that reflects the expectation of consumers [38]. At the same time, certain analysis has highlighted the fundamental real estate factors in any country in relation to loan availability, housing supply and dimet ratio, interest rate decrease, changes in housing market participants' expectations, administrative restrictions of supply, and so forth [39].

For the purpose of developing a prognostic model for the European real estate market, based on artificial neural networks, the authors suggested macroeconomic factors affected the real estate market. Training of the artificial neural network was carried out by defining 11 inputs and one output of the network (house price). The output variables—real estate prices for 27 EU countries—are provided on the basis of

available empirical data [36] and certain authors' calculations. Table 1 shows the basic inputs into the model and their definition and basic characteristics. Precollection and data analysis, preparation of data for defining the model, and, ultimately, the production of the model were performed.

The basic characteristics of the input and output parameters used for the training network represent 253 sets of data of which 80% are selected as a network training set and 20% as a validation set. All data is downloaded from the above-mentioned databases. After training the network was controlled on 11 sets of data on which the network was not trained.

The market value of real estate is subject to time changes and is determined at a certain date, so this prognostic model is time-dependent.

Creating an artificial neural network model trained to solve this problem consisted in defining network architecture with 11 variable inputs and one output. For network training, a two-layer neural network with two hidden layers of 15 neurons in the hidden layer was adopted.

Network training was conducted on a nonrecurrent network, while network training was carried out using an improved *Backpropagation* algorithm by periodically passing data from a training session through a neural network. The values obtained were compared with the actual outputs, and if the difference was made, correction of weight coefficients was made. Correction of weighing coefficients of the network was done by the rule of gradient downhill:

$$w_{ij}^{(l)\text{new}} = w_{ij}^{(l)\text{old}} - \eta \frac{\partial \varepsilon_k}{\partial w_{ij}^{(l)}}. \quad (1)$$

As an activation function, a logistic sigmoidal function was used:

$$f(x) = \frac{1}{1 + e^{-x}}. \quad (2)$$

Improving the *Backpropagation* algorithm meant introducing a moment so that the weight change in the period t would depend on the change in the previous period:

$$\Delta w_{ij}^{(l)}(t) = -\eta \frac{\partial \varepsilon_k}{\partial w_{ij}^{(l)}} + \alpha \Delta w_{ij}^{(l)}(t-1), \quad 0 < t < 1. \quad (3)$$

Network training was selected for a validation set of 20% of data. Training went to the moment of an error in the validation set so that the trained network showed good forecast performances.

The neural network is trained within the MS Excel program. Minor deviations from the training session are noted. Based on the network initiation with the input data from the range of data used in training, it is possible to draw up prognostic models of the dependence of the output from any input.

Control forecast was performed on 11 test datasets on which the network was not trained.

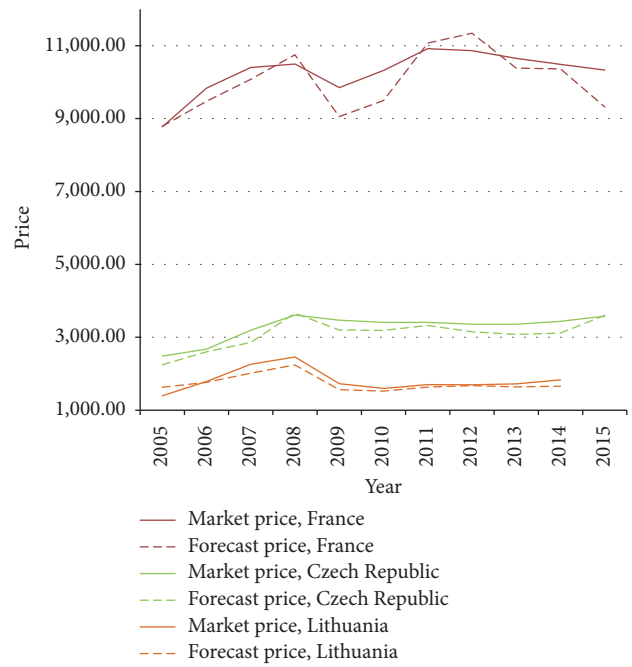

Figure 1: Deviation of the real price from the price forecast.

3. Results and Discussion

In general, our research has shown that prognostic models, based on the use of artificial neural networks, have a satisfactory degree of precision. Namely, the prognostic model for estimating the price of the real estate in the EU market, done for the purposes of this survey, is an average deviation of real price from a price forecast of up to 14%. Figure 1 shows this deviation for 3 selected countries of different level of development.

On the basis of the prognostic model, designed on the use of artificial neural networks, real estate prices in the EU countries were estimated, starting with the macroeconomic variables that were originally assumed to have a significant impact on the output variable. The analysis takes into account the impact of the change of a certain factor relevant to real estate prices in the EU market, with other unchanged real variables.

Figures 2, 3, and 4 show changes in forecasted real estate prices in countries with different levels of development (high, medium, and low) under the influence of GDP growth rates. In the countries surveyed, regardless of the degree of development, there is a trend of growth of forecasted real estate prices with an increase in the GDP growth rate. Theoretically, GDP growth rate can significantly increase the real estate price by increased consumption in the conditions of large housing infrastructure projects that are affecting employment growth. Mortgage payments are more acceptable, so real estate demand rises and ultimately increases real estate prices. Some research deals with the relationship between changes in real estate prices and changes in real GDP, or whether the interdependence between these two variables is statistically significant. The regression analysis method has indicated that

Table 1: Basic inputs into the model, their definition, and basic characteristics.

Variable	Variable definition (according to the sources given below this table)	Minimum	Maximum	Mean	Standard deviation	Unit of measure
GDP*	GDP (gross domestic product) reflects the total value of all goods and services produced less the value of goods and services used for intermediate consumption in their production.	5.142	3.032.820	477.763,56	720.649,35	mil €
BDP per capita*	GDP per capita at market prices is calculated as the ratio of GDP at market prices to the average population of a specific year.	4.200	84.400	23.829,63	15.759,46	€
Real GDP growth rate*	The calculation of the annual growth rate of GDP volume is intended to allow comparisons of the dynamics of economic development both over time and between economies of different sizes.	−14,8	11,9	1,63	3,84	%
Inequality of income distribution*	The ratio of total income received by the 20% of the population with the highest income (top quintile) to that received by the 20% of the population with the lowest income (lowest quintile).	3,2	8,3	4,83	1,16	-
Total unemployment rate*	Unemployment rates represent unemployed persons as a percentage of the labour force.	3,40	27,50	9,07	4,32	%
Average annual net earnings*	Net earnings are calculated from gross earnings by deducting the employee's social security contributions and income taxes and adding family allowances in the case of households with children.	1.550,77	38.490,18	17.175,81	10.445,15	€
FDI**	Foreign direct investment refers to direct investment equity flows in the reporting economy. It is the sum of equity capital, reinvestment of earnings, and other capital.	−29.679	734.010	27.948	67.501	mil $
HICP-inflation rate*	Harmonised Indices of Consumer Prices (HICPs) are designed for international comparisons of consumer price inflation.	−1,6	15,3	2,38	2,20	%
VAT (%)***	The value added tax, abbreviated as VAT, in the European Union (EU) is a general, broadly based consumption tax assessed on the value added to goods and services.	15	27	20,5	2,57	%
Taxes on property as % of GDP****	Tax on property is defined as recurrent and nonrecurrent taxes on the use, ownership, or transfer of property. These include taxes on immovable property or net wealth, taxes on the change of ownership of property through inheritance or gift, and taxes on financial and capital transactions.	0,283	5,387	1,463	1,06	%
Taxes on property as % of total taxation****		0,844	14,907	4,013	2,74	%

Sources. *Eurostat, **World Bank, ***ECB, and ****OECD and Eurostat.

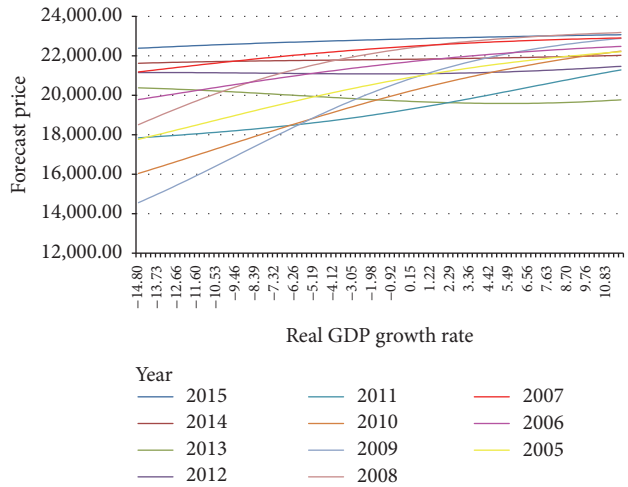

Figure 2: The impact of the real GDP growth on the real estate price forecast in the UK.

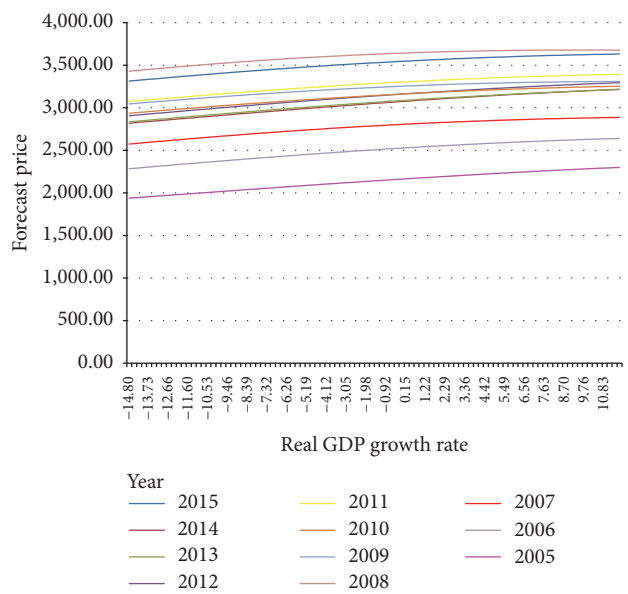

Figure 3: The impact of the real GDP growth rate on the real estate price forecast in Czech Rep.

there is a relationship and dependence, while the correlation suggests a possible causal interconnection between these variables [40]. In OLS (ordinary least squares) models, as well as in models based on the application of artificial neural networks, the GDP growth rate is taken as one of the key macroeconomic variables that affect the price of real estate with varying degrees of significance in different countries [29].

Figures 5, 6, and 7 show changes in the real estate prices forecast under the influence of the HICP. On the figures, it can be seen that, regardless of the degree of development of the country with the increase in HICP, there is a rise in the forecasted price of real estate. Some studies, such as those from Burinsena, Rudzkiene, and Venckauskaite, on the example of Lithuania, have shown that the HICP, as

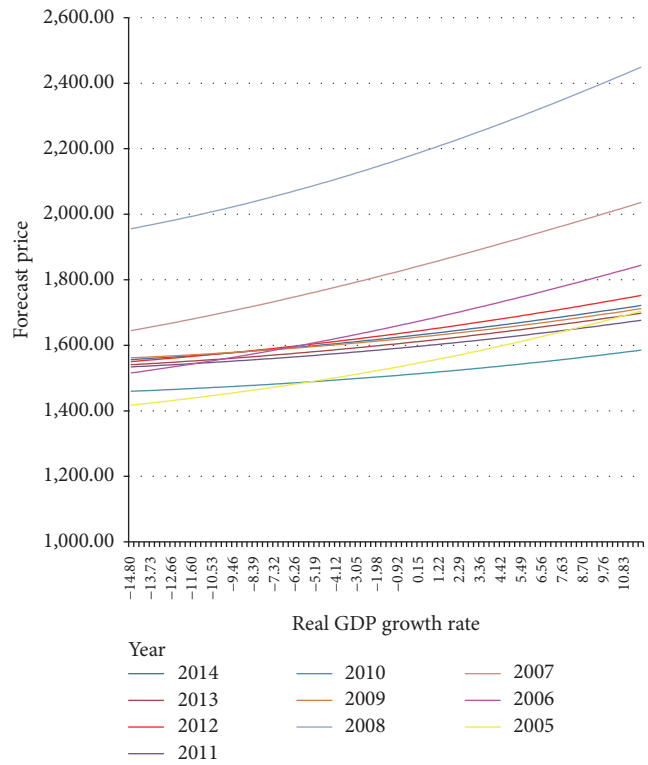

Figure 4: The impact of the real GDP growth rate on the real estate price forecast in Lithuania.

an indicator of the average annual inflation rate, is one of the main factors of the real estate market [39]. Also, some research conducted for highly developed countries (e.g., Norway case) have shown that a long-term increase in HICP has been accompanied by a rather sharp rise in real estate prices [41].

Figures 8, 9, and 10 show changes in the real estate prices forecast under the influence of the unemployment rate in countries with different levels of development. Figures for the surveyed countries indicate an apparent decline in the real estate prices forecast with an increase in the unemployment rate. In theory, the dominant views are that low unemployment leads to an income rise and affects the increase in consumer confidence that manifests itself on the real estate market, encouraging real estate prices growth and vice versa. Earlier empirical research on the impact of economic variables on property price dynamics has shown that growth in unemployment reduces real estate prices [42], as our prognostic model also pointed out. Certain recent empirical studies point to the undeniable impact of the unemployment rate, as a macroeconomic factor, on real estate prices. The impact of the unemployment rate on real estate prices differs from country to country. One of these studies has shown that the price of real estate in France, Greece, Norway, and Poland is statistically significantly associated with unemployment [43]. Also, research related to Ireland proves that at low levels of unemployment, real estate prices tend to grow [44].

Figures 11, 12, and 13 show changes in real estate prices forecast in countries with different levels of development

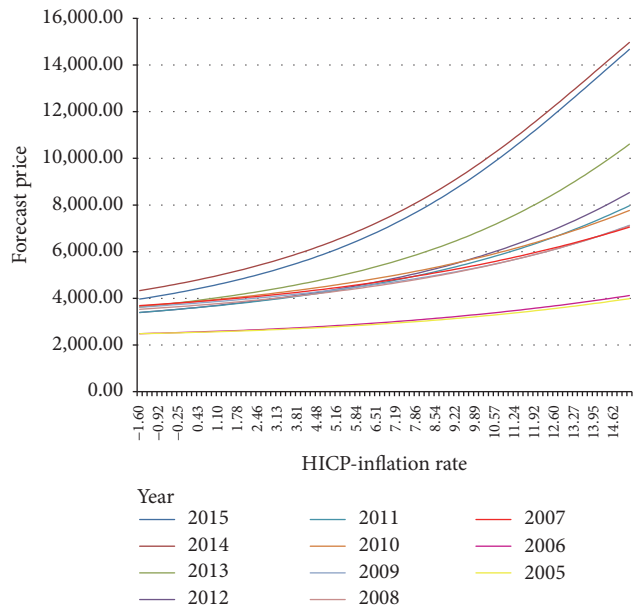

Figure 5: The impact of the HICP-inflation rate on the real estate price forecast in Germany.

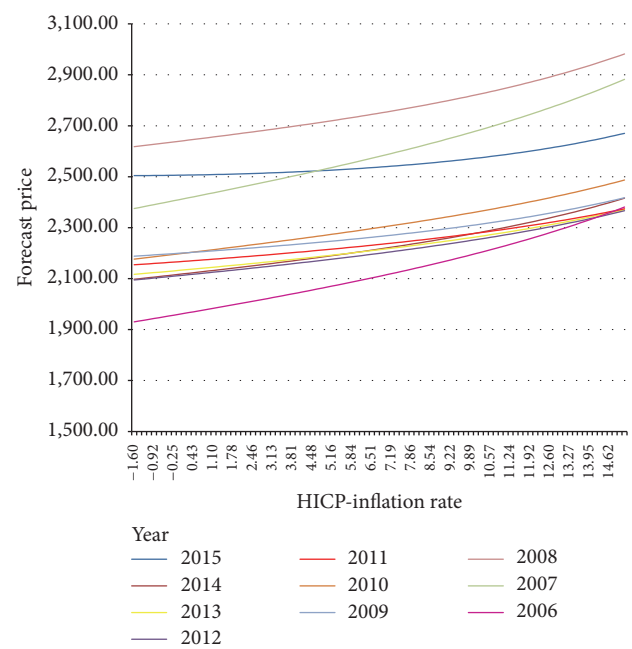

Figure 6: The impact of the HICP-inflation rate on the real estate price forecast in Slovakia.

(high, medium, and low developed) under the influence of average annual net earnings. The growth of average annual net earnings is followed by the growth of the output variable—real estate prices in the observed countries. Empirical researches have shown during the previous decades that the growth rate of income (earnings) is an essential determinant of the growth of real estate prices. Thus, in highly developed countries, income growth (earnings), at lower interest rates and slower lending conditions, is recognized

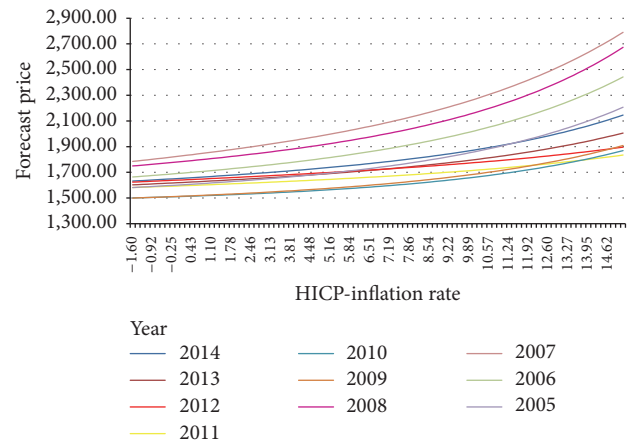

Figure 7: The impact of the HICP-inflation rate on the real estate price forecast in Lithuania.

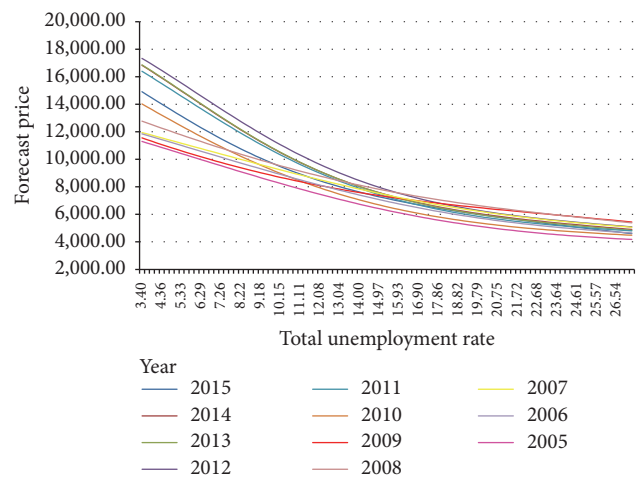

Figure 8: The impact of the total unemployment rate on the real estate price forecast in France.

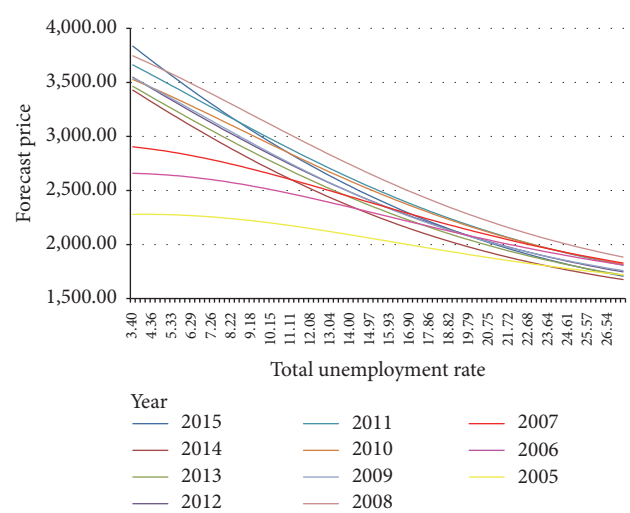

Figure 9: The impact of the total unemployment rate on the real estate price forecast in Czech Rep.

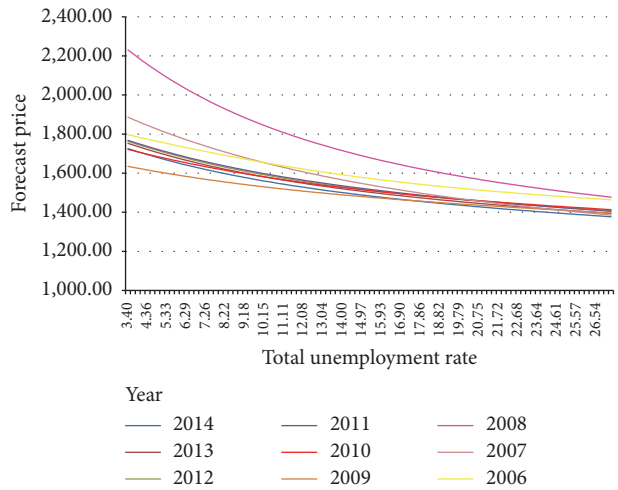

Figure 10: The impact of the total unemployment rate on the real estate price forecast in Bulgaria.

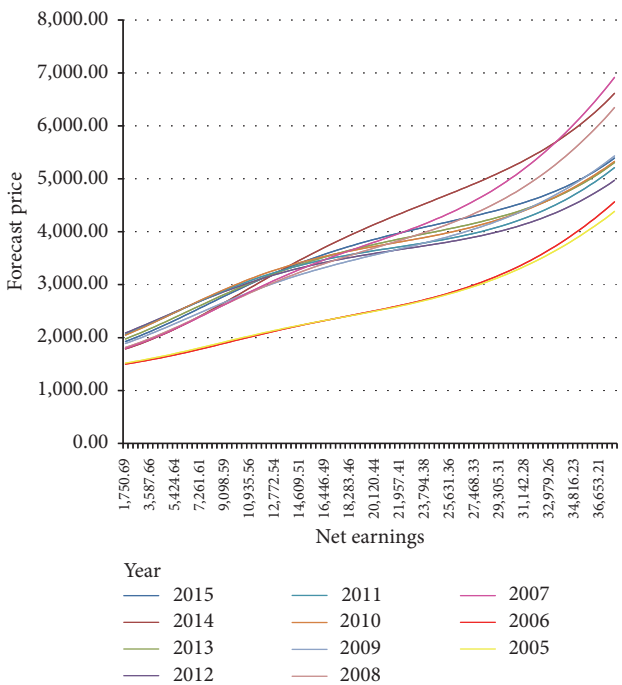

Figure 11: The impact of net earnings on the real estate price forecast in Germany.

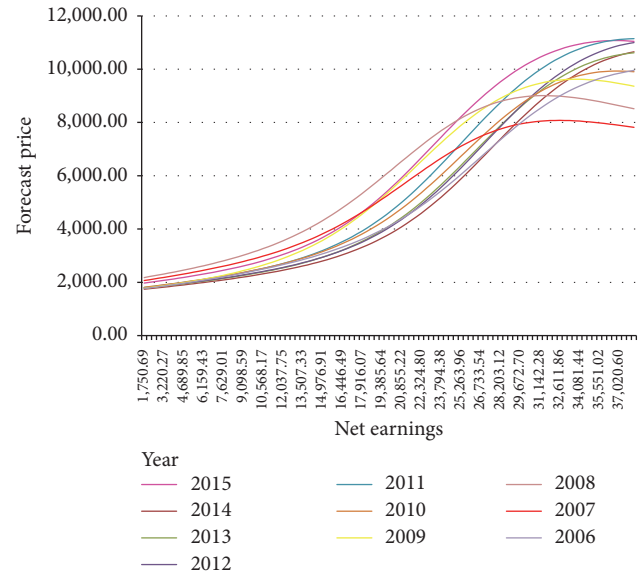

Figure 12: The impact of the net earnings on the real estate price forecast in Slovakia.

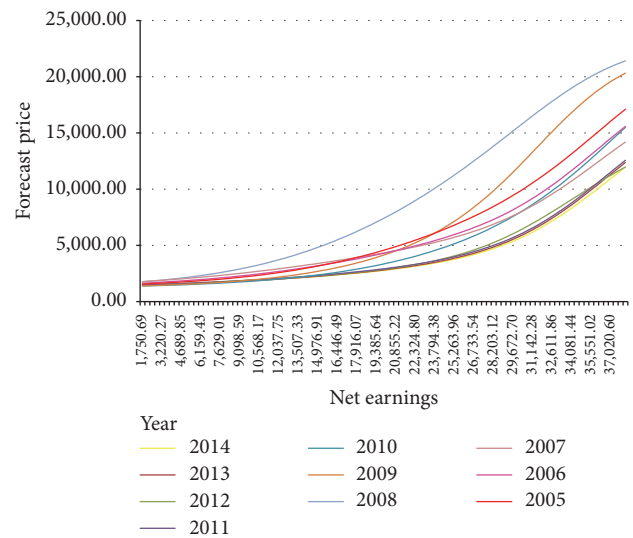

Figure 13: The impact of the net earnings on the real estate price forecast in Lithuania.

as a key factor in the rapid rise of the real estate prices [45]. Certain models, such as the P-W model, indicate that house prices are functions of the cyclical unemployment rate, income, demographics, costs of financing housing purchases, and costs of construction materials [46].

4. Conclusion

The economic and social importance of the real estate market corresponds to overall economic development, but the housing sector can also be the cause of vulnerability and crisis. Therefore, the problem of estimating the value of real estate is always current and complex due to the influence of a large number of variables that are recognized in the literature as usual as macroeconomic, construction, and other factors. Contrary to conventional real estate estimation methods, new approaches have been developed to evaluate prices in real estate markets. In addition to the hedonic method in the last decades, models of artificial neural networks that provide more objective and accurate estimates have been developed. This paper presents a prognostic model of real estate market prices for EU countries based on artificial neural networks.

For a rough and fast estimation of house prices with a reliability of about 85%, it is possible to use a trained neural network. We consider the obtained level of reliability as very

high, it is about modeling the sociotechnical system. More accurate pricing and reliable information could be obtained if a larger set of input parameters was included.

It is shown that the neural network can model nonlinear behavior of input variables and generalize real estate prices data for random inputs in the network training range. The model shows a satisfactory degree of forecasted precision which guarantees the possibility of its applicability.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] Y. Shachmurove, "Business application of emulative neural networks," *International Journal of Business*, vol. 10, no. 4, 2005.

[2] I. A. Basheer and M. Hajmeer, "Artificial neural networks: fundamentals, computing, design, and application," *Journal of Microbiological Methods*, vol. 43, no. 1, pp. 3–31, 2000.

[3] G. Zhang, B. E. Patuwo, and M. Y. Hu, "Forecasting with artificial neural networks: the state of the art," *International Journal of Forecasting*, vol. 14, no. 1, pp. 35–62, 1998.

[4] A. W. C. Oreta and K. Kawashima, "Neural network modeling of confined compressive strength and strain of circular concrete columns," *Journal of Structural Engineering*, vol. 129, no. 4, pp. 554–561, 2003.

[5] M. Lazarevska, M. Knežević, M. Cvetkovska, and A. Trombeva-Gavriloska, "Application of artificial neural networks in civil engineering," *Technical Gazette*, vol. 21, no. 6, pp. 1353–1359, 2014.

[6] M. Lazarevska, M. Kneževiá, M. Cvetkovska, N. Ivanišević, T. Samardzioska, and A. Trombeva-Gavriloska, "Fire-resistance prognostic model for reinforced concrete columns," *Gradjevinar*, vol. 64, no. 7, pp. 565–571, 2012.

[7] D. Bojović, D. Jevtić, and M. Knežević, "Application of neural networks in determination of compressive strength of concrete," *Romanian Journal of Materials*, vol. 42, no. 1, pp. 16–22, 2012.

[8] B. Šćepanović, M. Knežević, and D. Lučić, "Methods for determination of ultimate load of eccentrically patch loaded steel I-girders," *Informes de la Construcción*, vol. 66, no. 1, pp. 1–13, 2014.

[9] M. Knežević, M. Lazarevska, M. Cvetkovska, A. Trombeva-Gavriloska, and M. Milanović, "Neural network based approach for prediction the fire resistance of centrically loaded composite columns," *Technical Gazette*, vol. 23, no. 5, 2016.

[10] M. Knežević, D. Bojović, D. Nikolić, K. Jovanović, and L. Lončar, "The effect of entrapped air on concrete compressive strength- neural network approach and classical research," in *Proceedings of the 14th International Symposium of DGKM*, pp. 69–74, Struga, Macedonia, 2011.

[11] M. Lazarevska, M. Knežević, and M. Cvetkovska, "Application of artificial neural networks for prognostic modeling of fire resistance of reinforced concrete pillars," *Applied Mechanics and Materials*, vol. 148-149, pp. 856–861, 2011.

[12] S. A. Hamid, "Primer on using neural networks for forecasting market variables," in *Proceedings of the Conference at School of Business, Southern New Hampshire University*, 2004.

[13] I. Flood, "Simulating the construction process using neural networks," in *Proceedings of the 7th International Symposium on Automation and Robotics in Construction*, pp. 374–382, Bristol, UK, June 1990.

[14] D. S. Jeng, D. H. Cha, and M. Blumenstein, "Application of neural networks in civil engineering problems," in *Proceedings of the International Conference on Advances in the Internet, Processing, Systems and Interdisciplinary Research*, 2003.

[15] A. Mukherjee and J. M. Deshpande, "Modeling initial design process using artificial neural networks," *Journal of Computing in Civil Engineering*, vol. 9, no. 3, pp. 194–200, 1995.

[16] M. A. Shahin, H. R. Maier, and M. B. Jaksa, "Predicting settlement of shallow foundations using neural networks," *Journal of Geotechnical and Geoenvironmental Engineering*, vol. 128, no. 9, pp. 785–793, 2002.

[17] A. Sanad and M. P. Saka, "Prediction of ultimate shear strength of reinforced-concrete deep beams using neural networks," *Journal of Structural Engineering*, vol. 127, no. 7, pp. 818–828, 2001.

[18] R. J. Abrahart and L. M. See, "Neural network modelling of non-linear hydrological relationships," *Hydrology and Earth System Sciences*, vol. 11, no. 5, pp. 1563–1579, 2007.

[19] A. M. Elazouni, I. A. Nosair, Y. A. Mohieldin, and A. G. Mohamed, "Estimating resource requirements at conceptual design stage using neural networks," *Journal of Computing in Civil Engineering*, vol. 11, no. 4, pp. 217–223, 1997.

[20] J. Xie, J.-F. Qiu, W. Li, and J.-W. Wang, "The application of neural network model in earthquake prediction in East China," *Advances in Intelligent and Soft Computing*, vol. 106, pp. 79–84, 2011.

[21] J. Shaw, "Neural network resource guide," *AI Expert*, vol. 8, no. 2, pp. 48–54, 1992.

[22] R. A. Borst, "Artificial neural networks: the next modeling/calibration technology for the assessment community?" *Property Tax Journal*, vol. 10, no. 1, pp. 69–94, 1991.

[23] M. Mattos, P. Simoes, E. Zancam, N. Ferreira, and C. Cechinel, "A neurofuzzy approach for property value prediction," in *Proceedings of the 35th Conferencia Latinoamericana de Informatica (CLEI '08)*, 2008.

[24] D. Fischer and P. P. Lai, "Artificial neural networks and computer assisted mass appraisal," in *Proceedings of the 12th Annual Conference of the Pacific Rim Real Estate Society (PRRES '06)*, Auckland, New Zealand, January 2006.

[25] C. Bagnoli and H. C. Smith, "The theory of fuzzi logic and its application to real estate valuation," *The Journal of Real Estate Research*, vol. 16, no. 2, 1998.

[26] H. Kusan, O. Autekin, and I. Ozdemir, "The use of fuzzi logic in predicting house selling price," *Expert System Application*, vol. 37, no. 3, 2010.

[27] Ş. Yalpir and G. Özkan, "Fuzzy logic methodology and multiple regressions for residential real-estates valuation in urban areas," *Scientific Research and Essays*, vol. 6, no. 12, pp. 2431–2436, 2011.

[28] J. Zurada, "Non-conventional approaches to property value assessment," *Journal of Applied Business Research*, vol. 22, no. 3, 2006.

[29] M. Renigier-Bilozor and R. Wisniewski, "The impact of macroeconomic factors on residential property prices indices in Europe," *XLI Incontro di Studio del Ce.S.E.T*, pp. 149–166, 2013.

[30] R. Wisniewski, "Modeling of residential property prices index using committees of artificial neural networks for PIGS, the European-G8, and Poland," *Argumenta Oeconomica*, vol. 1, no. 38, 2017.

[31] L. Pi-Ying, "Analysis of the mass appraisal model," in *Proceedings of the 23rd Pan Pacific Congress of Appraisers, Valuers and Counselors*, San Francisco, Calif, USA, 2006.

[32] S. Peterson and A. B. Flanagan, "Neural network hedonic pricing models in mass real estate appraisal," *Journal of Real Estate Research*, vol. 31, no. 2, pp. 147–164, 2009.

[33] V. Limsombunchai, "House price prediction: hedonic price model vs. artificial neural network," in *Proceedings of the NZARES Conference*, Blenheim, New Zealand, June 2004.

[34] European Systemic Risk Board, "Vulnerabilities in the EU residential real estate sector," European System of Financial Supervision, 2016, https://www.esrb.europa.eu/pub/pdf/reports/161128_vulnerabilities_eu_residential_real_estate_sector.en.pdf.

[35] Global Property Guide, "Residential property investment research," http://www.globalpropertyguide.com/.

[36] Deloitte, "Property Index—overview of European residential markets," Deloitte Czech Republic, 2016, https://www2.deloitte.com/content/dam/Deloitte/cz/Documents/survey/Property_Index_2016_EN.pdf.

[37] S. Vanichvatana, "Thailand real estate market cycles: case study of 1997 economic crisis," *GH Bank Housing Journal*, vol. 1, no. 1, pp. 38–47, 2007.

[38] V. Rudzkienė and V. Azbainis, "Nekilnojamo turto rinkos evoliucijos pokyčiai pereinamosios ekonomikos sąlygomis," in *Proceedings of the Business, Management and Education Conference Program*, Vilnius Gediminas Technical University, Novemeber 2010.

[39] M. Burinskiene, V. Rudzkiene, and J. Venckauskaite, "Models of factors influencing the real estate price," in *Proceedings of the 8th International Conference on Environmental Engineering*, Vilnius Gediminas Technical University, Vilnius, Lithuania, May 2001.

[40] R. M. Valadez, "The housing bubble and the U.S. GDP: a correlation perspective," *Journal of Case Research in Business and Economics*, vol. 3, Article ID 10490, 2010.

[41] I. Johansen and R. Nygaard, "Owner-occupied housing in the Norwegian HICP," Tech. Rep. 2009/18, Statistics Norway, Oslo, Norway, 2009.

[42] J. Clapp and C. Giacotto, "The influence of economic variables on house price dynamics," *Journal of Urban Ecnomics*, vol. 36, pp. 116–183, 1993.

[43] B. Grum and D. K. Govekarb, "Influence of macroeconomic factors on prices of real estate in various cultural environments: case of Slovenia, Greece, France, Poland and Norway," *Procedia Economics and Finance*, vol. 39, pp. 597–604, 2016.

[44] M. Mernagh, "House prices and unemployment: a story of linked fortunes," Significance in Economics & Business, Royal Statistical Society and American Statistical Association, 2014.

[45] K. Sommer, P. Sullivan, and R. Verbrugge, "Run-up in the house price-rent ratio: how much can be explained by fundamentals?" Bureau of Labor Statistics, Working paper 441, 2011.

[46] J. Peek and J. A. Wilcox, "The baby boom, "pent-up" demand, and future house prices," *Journal of Housing Economics*, vol. 1, no. 4, pp. 347–367, 1991.

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Research Article

Development of ANN Model for Wind Speed Prediction as a Support for Early Warning System

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The impact of natural disasters increases every year with more casualties and damage to property and the environment. Therefore, it is important to prevent consequences by implementation of the early warning system (EWS) in order to announce the possibility of the harmful phenomena occurrence. In this paper, focus is placed on the implementation of the EWS on the micro location in order to announce possible harmful phenomena occurrence caused by wind. In order to predict such phenomena (wind speed), an artificial neural network (ANN) prediction model is developed. The model is developed on the basis of the input data obtained by local meteorological station on the University of Rijeka campus area in the Republic of Croatia. The prediction model is validated and evaluated by visual and common calculation approaches, after which it was found that it is possible to perform very good wind speed prediction for time steps $\Delta t = 1$ h, $\Delta t = 3$ h, and $\Delta t = 8$ h. The developed model is implemented in the EWS as a decision support for improvement of the existing "procedure plan in a case of the emergency caused by stormy wind or hurricane, snow and occurrence of the ice on the University of Rijeka campus."

1. Introduction

Today we are witnessing a high number of various natural harmful meteorological and hydrological phenomena, which increase every year with a greater number of casualties and damage to property and the environment. The impact of these disasters quickly propagates around the world irrespective of who or where we are [1]. To cope with such, a growing number of professionals and volunteers strive to help [2] by gaining knowledge and taking actions toward hazard, risk, vulnerability, resilience, and early warning systems, but such has not resulted in changing the practices of disaster management [3, 4]. Additionally, some natural hazards have continuous impact on a smaller scale, that is, location. Their rate of occurrence and the impact they make around bring importance of implementing the same disaster management principles as is on bigger scale.

In order to cope with such challenges, Quarantelli (1988) [5] argued that the preparation for and the response to disasters require well aligned communication and information flows, decision processes, and coordination structures. Such become basic elements of today's early warning systems (EWSs). According to the United Nations International Strategy for Disaster Reduction (UN/ISDR, 2006) [6], a complete and effective EWS includes four related elements: (i) risk knowledge, (ii) a monitoring and warning system service, (iii) dissemination and communication, and (iv) response capability.

Today, the implementation of artificial neural networks (ANN) in order to develop prediction models becomes very interesting research field. The usage of ANN in field of hydrology and meteorology is relatively new since the first application was noted in the early nineties. The first implementation of ANN in order to predict wind speed is noted by Lin et al. (1996) [7], Mohandes et al. (1998) [8], and Alexiadis et al. (1998) [9]. Also, in order to predict wind speed, recently numerous examples of ANN implementation are noted. Fonte et al. (2005) [10] in their paper introduced a prediction

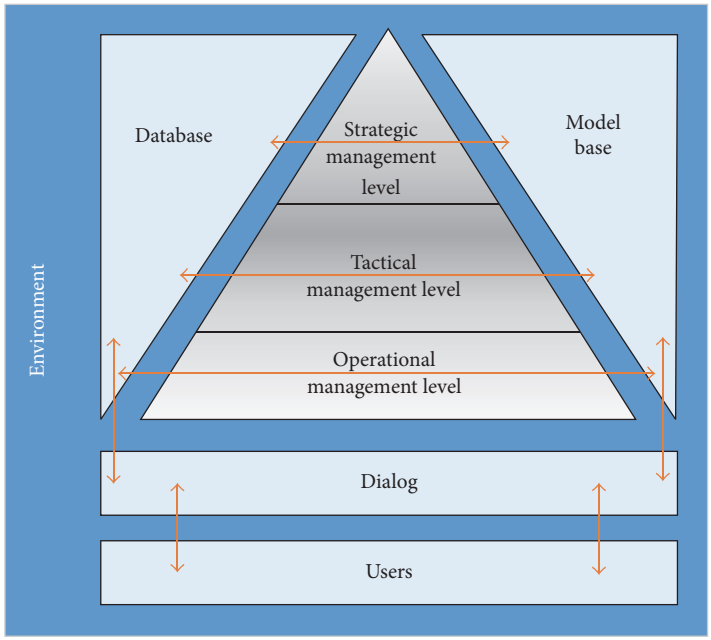

Figure 1: Structure of the decision support system for early warning management system.

of the average hourly wind speed, and Monfared et al. (2009) [11] in their paper introduced a new method based on ANN for better wind speed prediction performance presented. Pourmousavi Kani and Ardehali (2011) [12] introduced a very short-term wind speed prediction in their paper and Zhou et al. (2017) [13] presented a usage of ANN in order to establish the wind turbine fault early warning and diagnosis model. According to the aforementioned implementations of the ANN, development of such a prediction model in order to establish an EWS on the micro locations that are affected by the harmful effects of wind is not found and it needs to be better researched.

The goal of this research is to design and develop an ANN model in order to achieve a successful prediction of the wind speed on micro locations, based on data from local meteorological stations. The final aim and objective of the research is to implement a developed ANN wind speed prediction model in order to serve as decision support tool in an EWS.

This paper is organized as follows. Section 2 provides a research background of decision support as well as the methodology for development ANN prediction models as a tool for supporting decisions in EWS. In Section 3, the results of the proposed model are shown and discussed, with implementation in EWS on the micro location of University of Rijeka campus area. Finally, the conclusion and recommendations are presented in Section 4.

2. Methodology

Depending on the need of the business, different kinds of information systems are developed for different purposes. In general, different kinds of data and information are suitable for decision-making in different levels of organization hierarchy and require different information systems to be placed such as (i) Transaction Process Systems (TPS), (ii) Management Information Systems (MIS), (iii) Decision Support Systems (DSS), and (iv) Executive Support Systems (ESS) [16]. At the same time, each information system cannot fulfill complete information needs of each level. Therefore, overlapping of the systems is needed in order to preserve both information flows (from lower to upper level) and actions (from upper to lower level).

A structure of the proposed early warning management system (Figure 1) is based on Marović's previous research [17], where the "three decision levels" concept for urban infrastructure [18, 19] and spatial [17] management is proposed. The modular concept is based on DSS basic structure [20]: (i) database, (ii) model base, and (iii) dialog module. Interactions between modules are realized throughout the decision-making process at all management levels as they serve as meeting points of adequate models and data.

The first management level supports decision-makers at lowest operational management level. Beside its general function of supporting decision-making processes at operational level, it is a meeting point of data and information. Additionally, it provides information flows toward higher decision levels. It is a procedural level where problems are well defined and structured. The second management level deals with less defined and semistructured problems. On this level, tactical decisions are delivered, and it is a place where information basis and solutions are created. Based on applied models from model base (e.g., ANN), it gives alternatives and a basis for future decisions on strategic management level, which deals with even less defined and unstructured problems. At the third management level, based on the expert

deliverables from the tactical level, a future development of the system is carried out. Strategies are formed, and they serve as frameworks for lower decision and management levels.

Outside factors from the environment greatly influence decision support system, as is shown in Figure 1, on both decision-making and whole management processes. Such structure is found to be adequate for various urban management systems, and its structure easily supports all phases of the decision-making in early warning systems.

In addition to the previously defined four elements, EWSs are specific to the context for which they are implemented. Glantz (2003) [21] described general principles that one should bear in mind: (i) continuity in operations, (ii) timely warnings, (iii) transparency, (iv) integration, (v) human capacity, (vi) flexibility, (vii) catalysts, and (viii) apolitical. It is important to take into account current and local information [22] as well as knowledge from past events (stored in a database) or grown structures [23]. In order to be efficient in emergencies, EWSs need to be relevant and user-oriented and allow interactions between all tools, decision-makers, experts, and stakeholders [24–26]. It can be seen as an information system which deals with various types of problems (from structured to unstructured). The harmful event prediction model based on ANN is in general developed under the monitoring and warning system service and becomes a valuable tool in the DSS's model base.

The development of ANN prediction model requires a number of technologies and areas of expertise. It is necessary to have an adequate set of data (from monitoring and/or collection of existing historical data) on the potential hazard area, real-time, and remote monitoring of trigger factors. On such a collection of data, the data analysis is made, which serves as a starting point on the prediction model development (testing, validation, and evaluation processes) [27]. Importing such a prediction model in an existing or the development of a new decision support system results in a supporting tool for public authorities and citizens in choosing the appropriate protection measures on time.

2.1. Development of Data-Driven ANN Prediction Models. As a continuation of previous authors' research [14, 15], a new prediction model based on ANN will be designed and developed for the wind speed prediction as a base for the EWS. Nowadays, the biggest problem in the development of the prediction models is their diversity of different approaches to the modeling process, their complexity, procedures for model validation and evaluation, and implementation of different and imprecise methodologies that can in the end lead to practical inapplicability. Therefore, the aforementioned methodology [14, 15] is developed on the basis of the general methodology guidelines suggested by Maier et al. (2010) [28] and consists of the precise procedural steps. These steps allow implementation of the model on the new case study with a defined approach to complete modeling process.

Within this paper, steps of the methodology for the development of the ANN model are going to be briefly described, while in the dissertation done by Sušanj (2017) [15] the detailed description of the methodology can be found. The developed methodology consists of the four main process groups: (i) monitoring, (ii) modeling, (iii) validation, and (iv) evaluation.

2.1.1. Monitoring. The first process group of the aforementioned methodology is the monitoring group, which refers to the procedures of collecting relevant data (both historical and data from monitoring) and how it should be conducted. It is very important that the specific amount of the relevant and accurate data is collected as well as the triggering factors for the purpose of the EWS development to be recognized.

2.1.2. Modeling. The second group refers to the modeling process comprising the implementation of the ANN. In this process, identification of the model input and output data has to be determined. Additionally, data preprocessing, elimination of data errors and division of data into training, validation, and evaluation sets have to be done. When data is prepared, the implementation of the ANN can be conducted.

In the proposed methodology [14, 15], the implementation of the Multiple Layer Perceptron (MLP) architecture with three layers (input, hidden, and output) is recommended. The input layer should be formed as a matrix of a meteorological time series data multiplied by weight coefficient w_k that is obtained by learning algorithm in training process. The data should, in a hydrological and meteorological sense, have an influence on the output data. Therefore, it is very important that the input matrix is formed from at least ten previously measured data or one hour of measurements in each line of the matrix in order to allow the model insight into the meteorological condition in a given time period. The hidden layer of the model should consist of the ten neurons. The number of the neurons can be changed, but the previous research has shown that it will not necessary lead to model quality improvement. The output layer consists of the time series data that are supposed to be predicted. The model developer chooses the time prediction step, after which the process of the ANN training, validation, and evaluation can be conducted.

The quality and learning strength of the ANN model is based on the type of the activation functions and training algorithm that are used [29]. Activation functions are directing data between the layers and the training algorithm has the task of optimizing the weight coefficient w_k in every iteration of the training process in order to provide a more accurate model response. It is recommended to choose nonlinear activation function and learning algorithm because of their adaptation ability on the nonlinear problems. Therefore, bipolar sigmoid activation functions and the Levenberg-Marquardt learning algorithm are chosen. The schematic presentation for the ANN model development is shown in Figure 2.

After the architecture of the ANN model is defined and the training algorithm and prediction steps are chosen, the program packages in which the model will be programmed should be selected. There are a large number of the prepared program packages with prefabricated ANN models, but for this purpose completion of the whole programing process is advisable. Therefore, usage of the MATLAB (MathWorks, Natick, Massachusetts, USA) or any other programing software is recommended. After the model is programed, the

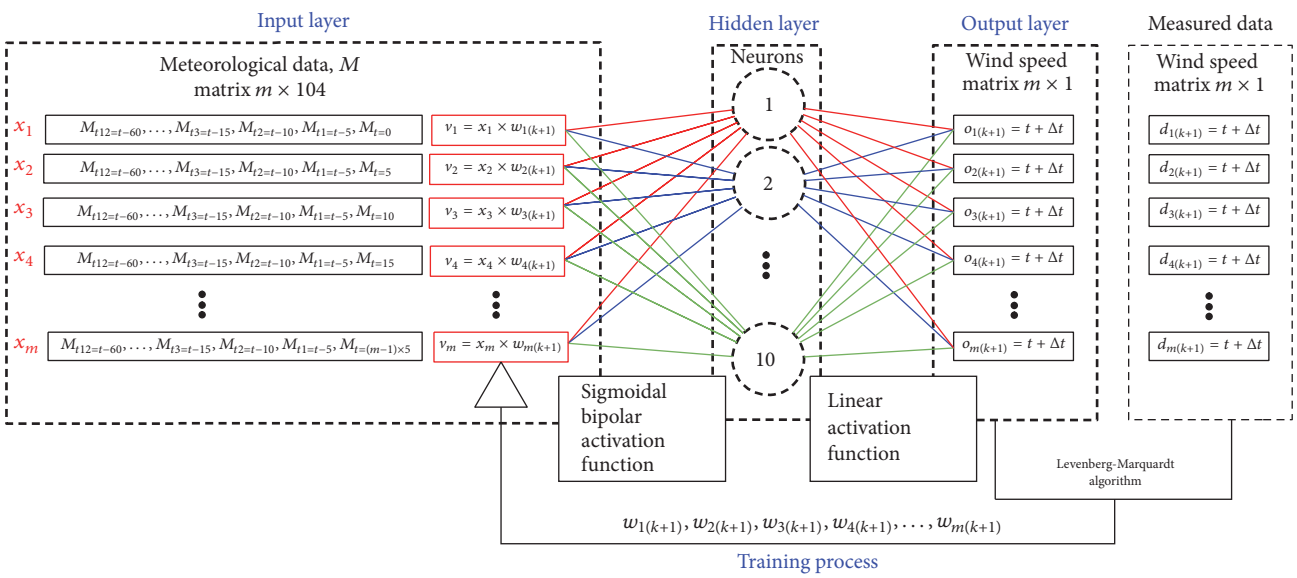

Figure 2: Schematic presentation of the artificial neural network prediction model ($x_{1,2,3,\ldots,m}$: input matrix data; $M_{t=(m-1)\times 5}$: input data set of meteorological data (wind speed, wind direction, wind run, high wind speed, high wind direction, air temperature, air humidity, and air pressure), $w_{1,2,3,\ldots,m}$: weight coefficient; v_k: sum of input matrix and weight coefficient products in kth iteration of the training process; o_k: neuron response for $t = \Delta t$ in kth iteration of the training process; d_k: measured data).

training process through the iterations of the calculation should be conducted.

2.1.3. Validation. The third group of the model development process refers to the model validation process. This is defined as the model's quality response as the training process is completed. The model should be validated with an earlier prepared set of the input and output data for that purpose (15% of data) in order to compare the model response with the measured data [29, 30]. The model response based on the validation data set has to be evaluated graphically and by applying numerical quality measures which are going to be appraised according to each used numerical model quality criteria. Therefore, it is advisable to use at least two numerical quality measures: (i) Mean Squared Error (MSE) and (ii) Coefficient of Determination (r^2).

2.1.4. Evaluation. The last group of the methodology steps refers to the model evaluation process, which is defined as the model's response quality on the data set that is not used in the training or validation process. The model should be evaluated with an earlier prepared set of the input and output data for that purpose (15% of data) in order to compare the model response with the measured data [29, 30]. The process of the model evaluation is similar to the process of the validation; the only difference is the number of numerical quality measures that are used in that process. In general, it is recommended [31] to use the following measures: (i) Mean Squared Error (MSE), (ii) Root Mean Squared Error (RMSE), (iii) Mean Absolute Error (MAE), (iv) Mean Squared Relative Error (MSRE), (v) Coefficient of Determination (r^2), (vi) Index of Agreement (d), (vii) Percentage to BIAS (PBIAS), and (viii) Root Mean Squared Error to Standard Deviation (RSR).

3. Results and Discussion

3.1. Location of the Research Area. The University of Rijeka campus area (hereinafter "Campus") is located in the eastern part of the city of Rijeka, Primorje-Gorski Kotar County, Republic of Croatia, and has an overall area of approximately 28 ha. At the location of the Campus permanently or occasionally stays around five thousand people (students and University employees) on a daily basis [33]. According to the specific geographical location, the Campus is known as a micro location affected by strong wind widely known by name of the Bura. It blows from the land toward the sea (Adriatic coastal area), mainly from the northeast, and by its nature is a strong wind (blowing in gusts). It usually blows for several days, and it is caused by the spilling of cold air from the Pannonian area across the Dinarid mountains toward coastline.

Since 2014, the Campus area has been affected by the wind Bura several times, causing damage to the Campus property and environment as is shown in Figure 3.

Because of flying objects that can cause damage to the property and the environment and hurt people and the powerful gusts of the wind Bura making it impossible for people to move outdoors, the "procedure plan in a case of the emergency caused by stormy wind or hurricane, snow and occurrence of the ice on the University of Rijeka campus" (hereinafter "procedure plan") was adopted in 2015.

3.2. Present State. This procedure plan was enacted according to the natural disaster protection law (NN 73/1997), and

(a) (b) (c) (d)

Figure 3: Damage on the Campus property and environment caused by the wind Bura: (a) and (b) damage in March 2015; (c) and (d) damage in January 2017.

the Campus Technical Services (CTS) is in charge of the procedure conduction. CTS has an obligation to monitor (i) wind speed and wind direction on the Campus area (installed measuring equipment) and (ii) the prediction of the Croatian official alerting system through the METEOALARM (Alerting Europe for extreme weather) obtained by the Network of European Meteorological Services (EUMETNET). According to the prediction alerting system and monitoring, CTS declares two levels of alert (Yellow and Red).

In the case of the stormy wind that is classified as wind with ten minutes' mean speed above 8 on a Beaufort scale ($v > 18{,}9$ m/s), the CTS will pronounce the first level of alert as "Yellow alert, stage of preparation for the emergency." The CTS will pronounce the second level of alert defined as "Red alert, extreme danger state of the natural disaster" in the case of a hurricane wind when the ten minutes' mean wind speed reaches 10 on a Beaufort scale ($v > 25$ m/s).

In the case of a Yellow alert, it is recommended to close the windows on the buildings and not be in the vicinity of possible flying objects and open windows. In the case of a Red alert, the area of the Campus is closed (postponing teaching and research activities) and people are not allowed to move outside of the buildings. The announcements are disseminated by e-mail to all University employees, through the local radio stations and on the official Internet web pages of every University constituent. The existing system alert is shown in Figure 4.

The implemented procedure plan is very simple and it has several deficiencies. As the procedure is not automated,

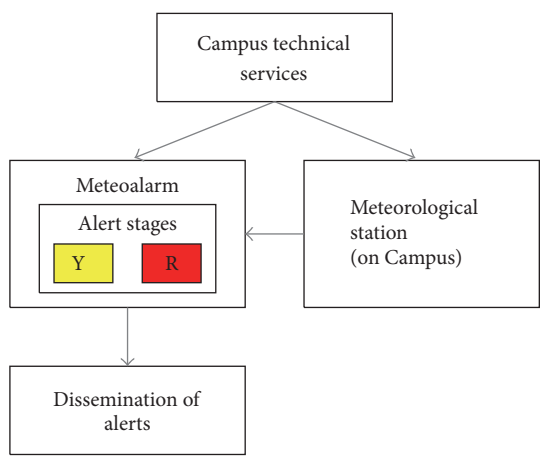

Figure 4: Scheme of the "procedure plan in a case of the emergency caused by stormy wind or hurricane, snow and occurrence of the ice on the University of Rijeka campus."

the dissemination of alerts is based on METEOALARM and the alertness of CTS employees to disseminate information. Bigger problems occur in METEOALARM's macro level of prediction as the possible occurrence of strong wind is not sufficiently accurate on the micro level due to the small number of meteorological stations in the region and versatile relief. The University of Rijeka campus area is placed on the specific micro location on which the speed of the wind gusts

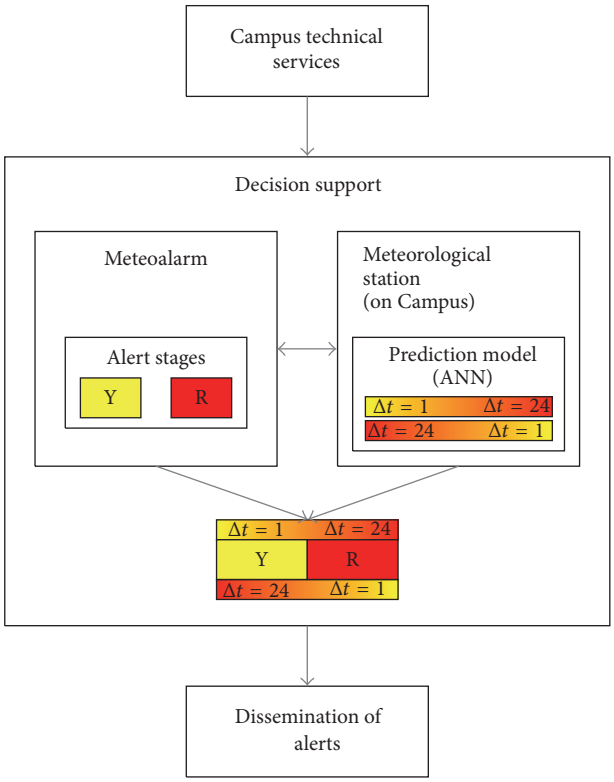

Figure 5: Scheme of the proposed EWS.

is usually greater than that in the rest of the wider Rijeka city area. The continuous monitoring and collection of the wind speed and direction data are implemented on the Campus area, but with those measurements it is only possible to see past and real-time meteorological variables such as wind speed and wind direction data. In this case, the real-time measurements are useless to the CTS in order to announce alerts on time, and they can serve only to observe the current state. The aforementioned location weather conditions imply that it is possible to have a stronger wind on Campus than that predicted by METEOALARM, which can potentially have a hazardous impact on both property and people. The dissemination of the announcements is also a weak part of the existing system because of the large number of the students that are not directly alerted.

Therefore, it is necessary to improve the existing alerting system by the implementation of the EWS that is going to be based on both the METEOALARM and the wind speed prediction model and also to improve the procedure plan by the development of the dissemination procedures to obtain better response capability. As the aim and objective is to design and develop an ANN model in order to achieve a successful prediction of wind speed on micro location, the focus of the proposed EWS (Figure 5) is on overlapping micro level prediction with macro level forecast.

As stated, a proposed procedure plan is based on METEOALARM's alert stages and real-time processed data from on-Campus meteorological station. Collected data from the meteorological station serve as input for ANN model, which gives results in the form of predicted wind speed in several time prediction steps. This provides an opportunity to the decision-maker to overlap predictions of ANN model of micro level with macro levels stages of alert in order to disseminate alerts toward stakeholders for specific locations. Therefore, micro level models can give an in-depth prediction on location. This is of great importance when there is a Yellow alert (on the macro level) and the ANN model predicts that conditions on the micro level are Red.

3.3. Data Collection. As mentioned before in the methodology for the development of the model, the first group of steps refers to the establishment of the monitoring. Therefore, continuous data monitoring of the meteorological variables has been established since the beginning of 2015. Data used for modeling purposes dated from January 1, 2015, to June 1, 2017. Meteorological variables used for prediction are (i) wind speed, (ii) wind direction, (iii) wind run, (iv) high wind speed, (v) high wind direction, (vi) air temperature, (vii) air humidity, and (viii) air pressure. They were collected by Vantage Pro 2 meteorological station (manufactured by Davis Instruments Corporation) that is installed on the roof of the Faculty of Civil Engineering. The measurement equipment is obtained by the RISK project (Research Infrastructure for Campus-Based Laboratories at the University of Rijeka; RC.2.2.06-0001). The frequency of data measurement interval is five minutes.

3.4. Development of ANN Wind Prediction Model. The aforementioned collected data is used for the development of the wind speed prediction model for the University of Rijeka campus area. Input (8 variables) and output (1 variable) of the model are selected and then preprocessed. Data is then divided into the sets for the training (70% of total data), validation (15% of total data), and evaluation (15% of total data) of the model. Statistics of data used for training, validation, and evaluation processes are shown in Table 1.

After data is prepared, implementation of the ANN model is conducted by MATLAB software (MathWorks, Natick, Massachusetts, USA), and the schematic representation of the model is shown in Figure 6.

Model training is conducted for the time prediction steps: (i) $\Delta t = 1$ h, (ii) $\Delta t = 3$ h, (iii) $\Delta t = 8$ h, (iv) $\Delta t = 12$ h, and (v) $\Delta t = 24$ h. After it is trained, the model is visually and numerically validated and evaluated. A comparison of the measured and predicted wind speed in the process of evaluation, according to time prediction step, is presented in Figure 7. On the basis of the visual analysis, it can be observed that the accuracy of the model decreases according to the extension of the prediction time step as expected.

Numerical validation and evaluation of the model are conducted according to the proposed aforementioned methodology. Results of the validation and evaluation processes and assessment of the model quality are shown in Table 2. Since some of the numerical model quality measures criteria are not precisely determined (measures: MSE, RMSE, MAE, MSRE, and RSR), it is recommended that the results should be close to zero. For others, used measures criteria are precise and models are assessed according to them.

Table 1: Statistics of data used for training, validation, and evaluation of the ANN wind prediction model.

Statistics*	Input layer								Output layer
	Wind speed	Wind direction	Wind run	High wind speed	High wind direction	Air pressure	Air humidity	Air temperature	Wind speed
	[m/s]	[ ]	[km]	[m/s]	[ ]	[hPa]	[%]	[°C]	[m/s]
Model training data (70% of data)									
n	156552	156552	156552	156552	156552	156552	156552	156552	156552
Max.	25,9	NNW	11,27	46	NNE	1036,9	98	41,4	25,9
Min.	0	/	0	0	/	972,5	11	−5	0
μ	2,68	/	0,83	4,98	/	1015,74	59,95	15,36	2,68
σ	2,53	/	0,82	4,42	/		21,16	8,2	2,53
Model validation data (15% of data)									
n	33547	33547	33547	33547	33547	33547	33547	33547	33547
Max.	21,9	NNE	6,57	38	NNE	1039,4	98	27,1	21,9
Min.	0	/	0	0	/	995,5	7	−8,1	0
μ	2,65	/	0,8	5,07	/	1021,49	65,14	8,18	2,65
σ	2,35	/	0,7	4,5	/	8,21	21,68	5,63	2,35
Model evaluation data (15% of data)									
n	33547	33547	33547	33547	33547	33547	33547	33547	33547
Max.	16,1	NNE	4,83	24,6	N	1034,7	97	37,1	16,1
Min.	0	/	0	0	/	997,9	14	0	0
μ	2,14	/	0,65	4,17	/	1016,7	57,86	16,02	2,14
σ	1,58	/	0,47	2,96	/	6,06	20,36	7,71	1,58

*n = number of observations; Max. = maximum; Min. = minimum; μ = sample mean; σ = standard deviation.

Table 2: Performance statistics of the ANN model during validation and evaluation processes.

Δt [h]	Validation		Evaluation							
	MSE	r^2	MSE	RMSE	MAE	MSRE	r^2	d	PBIAS	RSR
	[(m/s)^2]	[-]	[(m/s)^2]	[m/s]	[m/s]	[-]	[-]	[-]	[%]	[-]
1	0,075	**0,993**	0,058	0,158	0,113	23,34	**0,987**	0,998	**0,503**	0,105
3	2,033	**0,951**	1,505	0,736	0,581	1248,98	**0,894**	0,963	**6,817**	0,481
8	2,999	**0,868**	1,970	1,094	0,897	4365,318	*0,727*	0,85	*14,969*	0,729
12	3,872	**0,833**	2,306	1,216	1,026	3169,53	*0,669*	0,727	***17,302***	0,794
24	4,985	*0,572*	2,741	1,382	1,088	11166,16	***0,467***	0,353	*9,539*	0,923

Quality Criteria. Very good in bold, good in italic, and poor in bold italic. Model quality criteria according to [31, 32].

Numerical validation and evaluation measures have confirmed that the models with time steps $\Delta t = 1$ h, $\Delta t = 3$ h, and $\Delta t = 8$ h have noticeably better prediction possibilities since they are assessed as "very good" and "good" than models with time steps $\Delta t = 12$ h and $\Delta t = 24$ h. Additionally, other measures are very small, near zero, while for the time steps $\Delta t = 12$ h and $\Delta t = 24$ h they are significantly bigger. Although models with time steps $\Delta t = 12$ h and $\Delta t = 24$ h show poor quality results, according to visual analysis, they are still showing some prediction indication of an increase or decrease of wind speed, and therefore these predictions can be used, but carefully.

According to the results of performance statistics of the developed ANN model, the decision-maker on micro level can make decisions on time with up to prediction step of $\Delta t = 8$ h. By overlapping the macro level forecast with this micro level prediction, they can control the accurate dissemination of alerts in a specific area.

4. Conclusions

This paper presents an application of artificial neural networks in the predicting process of wind speed and its implementation in early warning system as a decision support

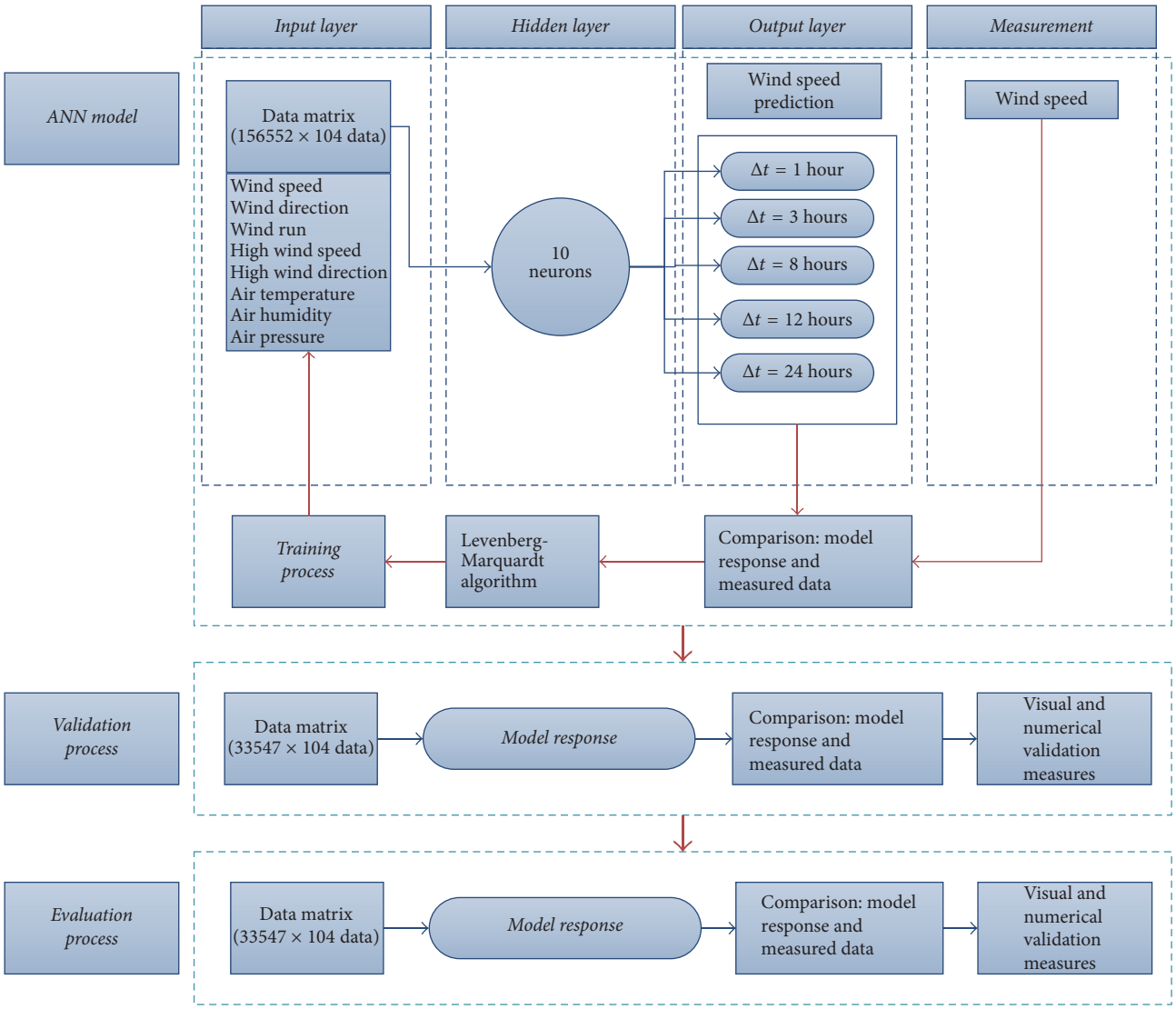

Figure 6: Schematic representation of the ANN wind speed prediction model based on [14, 15].

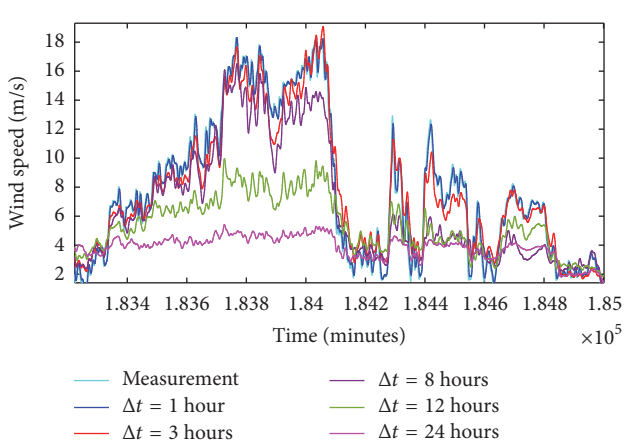

Figure 7: Comparison of the measured wind speed and model response (five minutes' time step) in process of the model evaluation according to time prediction steps ($\Delta t = 1$ h, $\Delta t = 3$ h, $\Delta t = 8$ h, $\Delta t = 12$ h, and $\Delta t = 24$ h).

tool. The main objectives of this research were to develop the model to achieve a successful prediction of wind speed on micro location based on data from meteorological station and to implement it in model base to serve as decision support tool in the proposed early warning system.

Data gathered by a local meteorological station during a 30-month period (8 variables) was used in the prediction process of wind speed. The model is developed for 5-time prediction steps: (i) $\Delta t = 1$ h, (ii) $\Delta t = 3$ h, (iii) $\Delta t = 8$ h, (iv) $\Delta t = 12$ h, and (v) $\Delta t = 24$ h. The evaluation of the model shows very good prediction possibilities for time steps $\Delta t = 1$ h, $\Delta t = 3$ h, and $\Delta t = 8$ h and therefore enables the early warning system implementation.

The performed research indicates that it is possible and desirable to apply artificial neural network for the prediction process on the micro locations, because that type of model is valuable and accurate tool to be implemented in model base to support future decisions in early warning systems.

The complete evaluation and functionality of the proposed early warning system and artificial neural network model can be done, after its implementation on the University of Rijeka campus (Croatia) is conducted.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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References

[1] A. De Bono, B. Chatenoux, C. Herold, and P. Peduzzi, *Global Assessment Report on Disaster Risk Reduction 2013: From Shared Risk to Shared Decision Support for Risk Management: Design of EWS 13 Value-The Business Case for Disaster Risk Reduction*, UNISDR, Geneva, Switzerland, 2013.

[2] Harvard Humanitarian Initiative et al. Disaster Relief 2.0, "The future of information sharing in humanitarian emergencies," HHI; United Nations Foundation; OCHA; The Vodafone Foundation, Washington DC, USA, 2010.

[3] J. C. Gaillard and J. Mercer, "From knowledge to action: Bridging gaps in disaster risk reduction," *Progress in Human Geography*, vol. 37, no. 1, pp. 93–114, 2013.

[4] J. Weichselgartner and R. Kasperson, "Barriers in the science-policy-practice interface: Toward a knowledge-action-system in global environmental change research," *Global Environmental Change*, vol. 20, no. 2, pp. 266–277, 2010.

[5] E. L. Quarantelli, "Disaster crisis management: a summary of research findings," *Journal of Management Studies*, vol. 25, no. 4, pp. 373–385, 1988.

[6] UN/ISDR platform for the promotion of early warning (PPEW) and un Secretairat of the International strategy for disaster reduction (UN/ISDR), "Developing early warning system: A checklist," in *Proceedings of the EWC III Third International Conference on Early Warning: From Concept to Action*, Bonn, Germany, March, 2006.

[7] L. Lin, J. T. Eriksson, H. Vihriala, and L. Soderlund, "Predicting wind behavior with neural networks," in *Proceedings of the 1996 European Wind Energy Conference*, pp. 655–658, Goteborg, Sweden, May 1996.

[8] M. A. Mohandes, S. Rehman, and T. O. Halawani, "A neural networks approach for wind speed prediction," *Journal of Renewable Energy*, vol. 13, no. 3, pp. 345–354, 1998.

[9] M. C. Alexiadis, P. S. Dokopoulos, H. S. Sahsamanoglou, and I. M. Manousaridis, "Short-term forecasting of wind speed and related electrical power," *Solar Energy*, vol. 63, no. 1, pp. 61–68, 1998.

[10] P. M. Fonte, G. X. Silva, and J. C. Quadrado, "Wind speed prediction using artificial neural networks," *WSEAS Transactions on Systems*, vol. 4, no. 4, pp. 379–383, 2005.

[11] M. Monfared, H. Rastegar, and H. M. Kojabadi, "A new strategy for wind speed forecasting using artificial intelligent methods," *Journal of Renewable Energy*, vol. 34, no. 3, pp. 845–848, 2009.

[12] S. A. Pourmousavi Kani and M. M. Ardehali, "Very short-term wind speed prediction: a new artificial neural network-Markov chain model," *Energy Conversion and Management*, vol. 52, no. 1, pp. 738–745, 2011.

[13] Q. Zhou, T. Xiong, M. Wang, C. Xiang, and Q. Xu, "Diagnosis and early warning of wind turbine faults based on cluster analysis theory and modified ANFIS," *Energies*, vol. 10, no. 7, article 898, 2017.

[14] I. Sušanj, N. Ožanić, and I. Marović, "Methodology for developing hydrological models based on an artificial neural network to establish an early warning system in small catchments," *Advances in Meteorology*, vol. 2016, Article ID 9125219, 14 pages, 2016.

[15] I. Sušanj, *Development of the hydrological rainfall-runoff model based on artificial neural network in small catchments [Ph.D. thesis]*, University of Rijeka, Faculty of Civil Engineering, Rijeka, Croatia, 2017.

[16] A. Asemi, A. Safari, and A. Asemi Zavareh, "The role of management information system (MIS) and decision support system (DSS) for manager's decision making process," *International Journal of Business and Management*, vol. 6, no. 7, pp. 164–173, 2011.

[17] I. Marovic, *Decision support system in real estate value management [Ph.D. thesis]*, University of Zagreb, Faculty of Civil Engineering, Zagreb, Croatia, 2013.

[18] N. Jajac, *Design of decision support systems in the management of infrastructure systems of the urban environment, [M.S. thesis]*, University of Split, Faculty of Economics, Split, Croatia, 2007.

[19] N. Jajac, S. Knezic, I. Marovic, S. Knezić, and I. Marović, "Decision support system to urban infrastructure maintenance management," *Organization, Technology & Managament in Construction*, vol. 1, no. 2, pp. 72–79, 2009.

[20] E. Turban, *Decision Support and Expert Systems: Management Support Systems*, Macmillan Publishing Company, New York, NY, USA, 1993.

[21] M. H. Glantz, *Usable Science 8: Early Warning Systems: Do's and Don'ts*, Report of Workshop, Shanghai, China, October 2003.

[22] Millennium Ecosystem Assessment, *Ecosystems and Human Well-Being: A Framework for Assessment*, Island Press, Washington, DC, USA, 2003.

[23] P. A. Schrodt and D. J. Gerner, "The impact of early warning on institutional responses to complex humanitarian crises," in *Proceedings of the Third Pan-European International Relations Conference and Joint Meeting with the International Studies Association*, Vienna, Austria, September 1998.

[24] P. Hall, "Early warning systems: Reframing the discussion," *Australian Journal of Emergency Management*, vol. 22, no. 2, 2007.

[25] UN/ISDR International Strategy for Disaster Reduction, "Hyogo framework for action 2005–2015: building the resilience of nations and communities to disasters," in *Proceedings of the World Conference on Disaster Reduction*, Hyogo, Japan, January, 2005.

[26] T. Comes, B. Mayag, and E. Negre, "Decision support for disaster risk management: integrating vulnerabilities into early-warning systems," in *Proceedings of the International Conference on Information Systems for Crisis Response and Management in Mediterranean Countries*, pp. 178–191, Springer International Publishing, Cham, Germany, October 2014.

[27] V. V. Krzhizhanovskaya, G. S. Shirshov, and N. B. Melnikova, "Flood early warning system: design, implementation and computational modules," *Procedia Computer Science*, vol. 4, pp. 106–115, 2011.

[28] H. R. Maier, A. Jain, G. C. Dandy, and K. P. Sudheer, "Methods used for the development of neural networks for the prediction of water resource variables in river systems: current status and future directions," *Environmental Modeling and Software*, vol. 25, no. 8, pp. 891–909, 2010.

[29] H. B. Demuth and M. H. Beale, *Neural Network ToolboxTM User's Guide*, The MathWorks, INC., 2004.

[30] M. T. Hagan, H. B. Demuth, M. H. Beale, O. De Jes, and O. De Jesús, *Neural Network Design (20)*, PWS Publishing Company, Boston, Mass, USA, 1996.

[31] R. Abrahart, P. E. Kneale, and L. M. See, *Neural Networks for Hydrological Modelling*, Taylor & Francis Group, London, UK, 2004.

[32] P. Matić, *Short-term forecasting of hydrological inflow by use of the artificial neural networks [Ph.D. thesis]*, University of Split, Faculty of Electrical Engineering, Mechanical Engineering And Naval Architecture, Split, Croatia, 2014.

[33] S. Grbac, L. Malnar, A. Vorkapić, D. Car-Pušić, and I. Marović, ""Preliminary analysis of the spatial attributes affecting students' quality of life at the University of Rijeka," in *Proceedings of the People, Buildings and Environment 2016, an International Scientific Conference*, vol. 4, pp. 109–117, Luhačovice, Czech Republic, 2016.

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Research Article

Estimation of Costs and Durations of Construction of Urban Roads Using ANN and SVM

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Offer preparation has always been a specific part of a building process which has significant impact on company business. Due to the fact that income greatly depends on offer's precision and the balance between planned costs, both direct and overheads, and wished profit, it is necessary to prepare a precise offer within required time and available resources which are always insufficient. The paper presents a research of precision that can be achieved while using artificial intelligence for estimation of cost and duration in construction projects. Both artificial neural networks (ANNs) and support vector machines (SVM) are analysed and compared. The best SVM has shown higher precision, when estimating costs, with mean absolute percentage error (MAPE) of 7.06% compared to the most precise ANNs which has achieved precision of 25.38%. Estimation of works duration has proved to be more difficult. The best MAPEs were 22.77% and 26.26% for SVM and ANN, respectively.

1. Introduction

Civil engineering presents a specific branch of industry from all aspects. The main reason for this lies in specific features of construction objects as well as the conditions for their realisation. Another specific aspect of realisation of construction projects is that the realisation process involves a large number of participants with different roles. The key role in the realisation of construction processes is certainly played by an investor, who is at the same time the initiator of realisation of a construction project, whose main goal is to choose a reliable contractor who can guarantee the fulfilment of set requirements (costs, time, and quality).

When choosing a constructor, a dominant parameter is the offered cost of realisation, which implies that it is necessary to carry out an adequate estimation of construction costs. The question that arises is which costs, that is, which price, should be the subject of estimation. Gunner and Skitmore [1] and Morrison [2] based their research which relates to the estimation of realisation costs, on the lowest price offered. However, according to Skitmore and Lo [3], very often the lowest price does not reflect actual realisation costs, since contractors offer services at unrealistically low prices. Azman et al. [4] quote the recommendation of Lowe and Skitmore to accept the second lowest offer, as the very lowest one does not guarantee the actual value. They also mention the suggestion made by McCaffer to use the mean value of submitted offers for estimation, rather than the lowest one, explaining that it is the closest to the actual price.

Some authors, however, Aibinu and Pasco [5], use the values given in the accepted offer for the needs of estimating the accuracy of predicted values, since it is the value accepted by the investor. Abou Rizk et al. [6] and Shane et al. [7] recommend the use of actually paid realisation value. Nevertheless, Skitmore [8] explains that there are certain problems when using actually paid values for realisation, with the main one residing in the fact that the data is not easily available, and even if they are, they are often not properly recorded, that is, are not real. Moreover, there is a problem of time between the forming of cost estimation and realisation of real costs, in which significant changes in the project may occur during the realisation process, which can influence the amount of contracted works for which the offer was formed.

According to everything mentioned above, the estimation of costs within this research was carried out based on the realisation value offered by the contractor.

Further on, there are two levels of estimation of potential works from the perspective of a contractor, which precede the realisation of contracting, and those are conceptual (rough) and preliminary (detailed) estimation [9]. Conceptual estimation of costs usually results in the total number without the detailed analysis of the structure of costs. This implies that conceptual estimation should use simpler and specialised estimation models. Its contribution is the assessment of justifiability of following work on the project in question, or more precisely further work on preliminary estimation which is carried out prior to signing of a contract. The basis for both estimations is the data about the object provided by the investor, that is, tender documentation. The question arises on what accuracy of estimation is acceptable. The required, acceptable accuracy of estimation of construction costs from the perspective of a contractor in the initial phase of tender procedure (conceptual estimation) according to Ashworth [10] amounts to ±15%. This is the accuracy which was adopted in this research as the basic goal of precision of formed models for the estimation of construction costs.

It was noted that the dominant parameter for choosing the most favourable contractor is the offered price. However, the proposed time for realisation of works in question should not be neglected either. The main problem of estimation of duration of works in the conceptual phase is the fact that the potential contractor does not possess realisation plans, which implies the application of estimation methods which provide satisfactory accuracy based on data available at a time. It is a common case for an investor to limit the maximum duration of construction in the tender conditions.

Having in mind that it is necessary to carry out simultaneous estimation of costs and duration of the construction process, the fact that the research confirmed that the costs of significant position of works are at the same time of temporal significance is highly important [11, 12]. The previously mentioned statement is significant for the processes of planning and control of time during the realisation of a construction project and confirms the justifiability of simultaneous estimation of costs and duration of contracted works.

It was mentioned that conceptual estimation requires application of simpler and specialised models with an acceptable accuracy of estimation. One of the possible approaches is the application of artificial intelligence (artificial neural networks (ANNs), support vector machine (SVM), etc.). The basic precondition for the application of this approach is the forming of an adequate base of historical data on similar construction projects previously realised.

2. ANN and SVM Applications in Construction Industry

The first scientific article related to the application of ANNs in construction industry was published by Adeli in the Microcomputers in Civil Engineering magazine [13]. The application becomes more frequent along with software development. The sphere of application of ANNs and the SVM in construction industry is very wide and present in basically all phases of realisation of a project, from its initialising, through designing and construction, to maintenance, renovation, demolishing, and recycling of objects. Some of the examples of their application are estimation of necessary resources for realisation of projects [14], subcontractor rating [15], estimation of load lifting time by using tower cranes [16], noting the quality of a construction object [17], application in carrying out of economic analysis [18], application in the case of compensation claims [19, 20], construction contractor default prediction [21], prequalification of constructors [22], cash flow prediction [23], project control forecasting [24], estimation of recycling capacity [25], predicting project performance [26], and many others.

Cost estimation by using ANNs and SVM is often represented in the literature, for example, estimation of construction costs of residential and/or residential-commercial facilities [27, 28], cost estimation of reconstruction of bridges [29], and cost estimation of building water supply and sewerage networks [30]. In his master thesis, Siqueira [31] addresses the application of ANN for the conceptual estimation of construction costs of steel constructions. An et al. [32] showed the application of SVM in the assessment process of construction costs of residential-commercial facilities. In addition to the mentioned authors, the application of ANNs and SVM for the estimation of construction costs was dealt with by Adeli and Wu [33], Wilmot and Mei [34], Vahdani et al. [35], and many others.

Kong et al. [36] carried out the prediction of cost per m^2 for residential-commercial facilities by using SVM. Kong et al. [37] carried out the comparison of results of price prediction for the same data base by using a SVM model and RS-SVM model (RS, rough set).

Kim et al. [38] carried out a comparative analysis of results obtained through ANN, SVM, and regression analysis for cost estimation of school facilities. This presents a rather common case in available and analysed literature. Not only the comparative analysis of ANN an SVM models with other models for solving of the same types of problems, but also its combining with other forms of artificial intelligence, such as fuzzy logic (FL) and genetic algorithms (GA), is carried out, where the so-called hybrid models are created. Kim et al. [39] compared models for cost estimation of the construction of residential facilities, based on multiple regression analysis (MRA), artificial neural networks (ANNs), and case-based reasoning (CBR). Sonmez [40] also drew a parallel between an ANN model for conceptual estimation of costs with a regression model. Kim et al. [41] and Feng et al. [42] used genetic algorithms (GA) in their research when defining an ANN model for cost estimation of construction of buildings, as a tool for optimisation of the ANN model itself. In addition to combining with GA, there is also the possibility of combining an ANN with fuzzy logic (FL), where hybrid models are created as well. The application of ANN-FL hybrid models for the estimation of construction costs was used in the research of Cheng and Huang [43] and Cheng et al. [44]. Cheng and Wu [45] outlined the comparative analysis of models for conceptual estimation of construction costs, formed by using of ANN, SVM, and EFNIM (evolutionary fuzzy neural inference model). Deng and Yeh [46] showed the use of LS-SVM (LS, least squares) model in the cost prediction process. Cheng et al. [47] connected two approaches of artificial

intelligence (fast genetic algorithm (fmGa) and SVM) for the purpose of estimation of realisation of construction projects (e.g., prediction of % completeness of *i*th, period in the realisation of the construction project). This model is called ESIM (evolutionary support vector machine inference model).

Since the topic of the research is the estimation of costs and duration of construction of urban roads, the following text will contain research carried out on similar types of constructions. Wang et al. [48] showed in their work the estimation of costs of highway construction by using ANNs. Including the set of 16 realised projects, they carried out the training (first 14 projects) and validation (remaining 2 projects) of the ANN model. Al-Tabtabai et al. [49] surveyed five expert project managers, defining the factors which influence the changes in the total costs of highway construction, such as location, maintaining of the existing infrastructure, type of soil, consultant's capability of estimation, construction of access roads, the distance of material and equipment transportation, financial factors, type of urban road, and the need for obtaining of a job.

Hegazy and Ayed [50] provided an overview of forming of a model by using ANNs for the parameter estimation of costs of highway construction. They use the data obtained from 18 offers by anonymous bidders for the realisation of works on highway construction in Canada, 14 offers for training, and 4 offers for testing. Sodikov [51] gave an outline of the estimation of costs of highway construction by applying ANNs. The analysis and formation of model were performed based on two sets of data from different locations. The first set of data was formed based on the projects realised in Poland (the total of 135 projects, with 38 realised projects on highway construction used for the analysis) and the second based on projects realised in Thailand (the total of 123 projects, with 42 realised projects on asphalt layer "coating"). It is important to note that Hegazy and Ayed [50] as well as Sodikov [51], used the duration of works realisation as the input parameter. This duration is also unknown in the process of defining of the conceptual estimation, as is the cost of realisation of works. El-Sawahli [52] performed the estimation of costs of road construction by using a SVM model formed according to the base of 70 realised projects in total.

Estimation of duration of the construction of buildings by using ANNs and SVM is not present in the literature, as it is the case with estimation of costs. Attal [53] formed independent and separate ANN models for estimation of costs and duration of highway construction. Bhokha and Ogunlana [54] defined an ANN model for prediction of duration of multistorey buildings construction in a preproject phase. Hola and Schabowicz [55] carried out the estimation of duration and costs of realisation of earthworks by using an ANN model. Wang et al. [56] performed the predicting of construction cost and schedule success by applying ANN and SVM.

3. Material and Methods

Within the research carried out, gathering of data and data analysis were performed, followed by the preparation of data for the needs of model formation, as well as the final forming of models and their comparative analysis.

Gathering of data and forming of the data base on realised construction projects of reconstruction and/or construction of urban roads were carried out on the territory of the city of Novi Sad, the Republic of Serbia. All the projects were funded by the same investor in the period between January 2005 and December 2012. All the projects solely relate to the realisation of construction works based on completed projects and technical documentation. Having in mind everything mentioned above, uniform tender documentation, that is, the bill of works which makes its integral part, served as the main source of information.

The sample comprises 198 contracted and realised construction projects. However, not all of the projects were included in the analysis carried out later on, owing it to the fact that certain projects, 32 of them in total, include realisation of works on relocation of installations (sewerage, water, gas, etc.), green spaces landscaping, street lighting, and construction of supporting facilities on the roads (smaller bridges, culverts, etc.), which are excluded from further analysis.

The total number of realised projects included in the further analysis amounts to 166 projects of basic construction works and/or reconstruction of urban roads. As it has been already noted, all projects were realised for the same investor. Consequently, the tender documentation is uniform, which is also the case with the distribution of works within the bill of works, dividing them into preparation works, earthworks, works on construction of pavement and landscaping, drainage works, works on construction of traffic signals, and other works.

The analysis of the share of costs of the mentioned work groups in the total offered price of realisation was carried out. This confirmed that the works on roadway structure and landscaping have the biggest impact on the total price, ranging within the interval from 22.24% to 100% (only two cases where only these two types of works were planned). Earlier research included similar analysis, but only for projects realised by the same contractor [57, 58].

Table 1 shows mean values of the percentage of works groups in the total offered value for realisation of works. The interval between 65% and 95% of the amount of works on the roadway construction and landscaping within the total offered price includes 106 projects, that is, 63.86% of the total number of analysed projects. The total number of potential work positions which may occur during the realisation of all basic works is 91 (according to the general section of tender documentation, which is the same for all analysed projects), whereas the total number of potential positions from the bill of works related to roadway construction and landscaping works amounts to 18. Percentage share of activities related to roadway construction and landscaping in relation to the total number of potential positions amounts to 19.78%, which is approximately the same as the percentage of cost-significant activities according to "Pareto" distribution, which amounts to 20%.

Considering the fact that for 63.86% of analysed projects the share of the total price ranges within the interval between ±15% and 80% of the total offered value, it can be stated that the works on roadway construction and landscaping are

Table 1: Mean values of the percentage of works groups in the total offered value.

Number	Group of works	Mean value of the percentage of works groups in the total offered price [%]
(1)	Roadway construction and landscaping works	68
(2)	Earthworks	14
(3)	Preparation works	12
(4)	Other works	3
(5)	Drainage works	2
(6)	Works on traffic signals installation	1

Table 2: Number of projects according to the offered number of days for realisation.

Number	Offered number of days	Number of projects	Percentage share in the data base [%]
(1)	Up to 20	50	30.12
(2)	21 to 30	31	18.67
(3)	31 to 40	24	14.46
(4)	41 to 50	26	15.66
(5)	51 to 60	14	8.43
(6)	61 to 70	5	3.01
(7)	71 to 80	7	4.22
(8)	81 to 90	4	2.41
(9)	Above 90	5	3.01

cost-significant according to "Pareto" distribution, that is, distribution of 20/80. This is an additional reason why these works play the major role when defining an estimation model. Realisation of works on roadway construction and landscaping relates to usage of basic materials, such as crushed stone (different fractions), curbs, asphalt base layer, asphalt surface layer, and concrete prefabricated elements for paving.

Duration of realisation is offered in the form of the total number of days and there is no way in which it can be claimed with certainty how much time is needed for the realisation of each group of works individually. For this reason, classification of projects was carried out based solely on the total amount of time offered for the realisation of all planned works. Table 2 shows the number of projects according to the offered number of days for realisation. According to some research, cost-significant work positions are duration-significant as well [11, 12]. Hence, it is of equal importance to put particular emphasis on works related to roadway construction and landscaping, both from the perspective of cost estimation and from the duration of the realisation process.

Estimation of costs, as well as all the other estimations such as duration of realisation, involves the engagement of resources. According to the literature, estimation of costs ranges between 0.25% and 1% of the total investment value [59]. For this reason, Remer and Buchanan [60] developed a model for estimating of costs for the work (cost) estimation process. The reason for such research lies in the fact that low-cost estimates can lead to unplanned costs in the realisation process and/or in lower functional features of an object than those required by the investor.

The primary purpose of forming of an estimation model is to perform the most accurate estimation possible in the shortest interval of time possible, with the minimum engagement of resources, all of it based on the data available at the time of estimation. Since the contracts in question are the so-called "build" contracts, an integral part of tender documentation is the bill of works, or more precisely the amount of works planned in the project-technical documentation. Estimations of costs based on amounts and unit prices are the most accurate ones but require a great amount of time and need to be applied in preliminary (detailed) estimation, which precedes directly the signing of a contract. However, conceptual (rough) estimation which results in the total costs of realisation requires simpler and faster methods of estimation. With the aim of defining a method featuring such performances, a formerly presented analysis of significance and impact of groups of works on the total price, both on total costs and on realisation time, was carried out.

The works on roadway construction and landscaping, as the most important group of works, were considered in more detail in comparison with other groups of works; that is, they were assigned greater significance. Having in mind the characteristics of works performed within this group, a large amount of material necessary for their realisation being one of them, the input parameters for creating of this model are the amounts of material necessary for their realisation (Table 4).

Despite the fact that the mean percentage share of roadway construction and landscaping works amounts to 68%, the share of the remaining groups of works in the total

Table 3: Number of projects depending on the offered revalorised price for realisation of works.

Number	Offered price for realisation [RSD]*	Number of projects	Percentage share in data base [%]
(1)	Up to 5,000,000	32	19.2
(2)	From 5,000,000 to 10,000,000	28	16.87
(3)	From 10,000,000 to 20,000,000	24	14.46
(4)	From 20,000,000 to 30,000,000	19	11.45
(5)	From 30,000.000 to 40,000,000	13	7.83
(6)	From 40,000,000 to 60,000,000	8	4.82
(7)	From 60,000,000 to 100,000,000	21	12.65
(8)	From 100,000,000 to 200,000,000	13	7.83
(9)	Over 200,000,000	8	4.82

*RSD: Republic Serbian Dinar (1 EUR = 122 RSD).

Table 4: Inputs into models.

Number	Description of input data	Data type	Unit of measurement	Min	Max	Mean value
Input 1	Amount of crushed stone	Numerical	m^3	0,00	16,070.00	1,694.62
Input 2	Amount of curbs	Numerical	m^1	0,00	14,300.00	1,975.07
Input 3	Amount of asphalt base layer	Numerical	t	0,00	31,569.00	1,119.61
Input 4	Amount of asphalt surface layer	Numerical	t	0,00	11,046.00	505.85
Input 5	Amount concrete prefabricated elements	Numerical	m^2	0,00	20,000.00	2,824.85
	Percentage share of wok positions					
Input 6	Preparation works	Numerical	%	0,00	100.00	43.18
Input 7	Earthworks	Numerical	%	0,00	100.00	48.92
Input 8	Drainage works	Numerical	%	0,00	93.33	16.63
Input 9	Traffic signalisation works	Numerical	%	0,00	100.00	28.66
Input 10	Other works	Numerical	%	0,00	100.00	8.59
Input 11	Works realisation zone	Discrete	-	1	2	-
Input 12	Project category (values of up to and over 40,000,000)	Discrete	-	1	2	-

offered value should not be neglected. The biggest share in the total offered value for realisation of the remaining groups of works belongs to earthworks and preparation works, whereas traffic signals, other works, and drainage contribute with a considerably lower percentage (Table 2).

Inclusion of the mentioned works in further analysis was carried out based on the number of planned positions of works for each individual bid project in relation to a possible number of positions of works (according to a universal list issued by the investor) in groups of works, directly through percentage share (Table 4).

Moreover, it was noticed that it is possible to classify realised works based on the location they were supposed to be realised on. For that purpose, realisation of works was divided into two zones: zone 1, realisation of works in the city centre, and zone 2, realisation of works in the suburbs (Table 4).

Since the research carried out relates to the financial aspect of realisation of construction projects, it is necessary to perform revalorisation, in order for the data to be comparable and applicable to forming of an estimation model by using artificial intelligence. By using the revalorisation process, defining of difference is achieved, that is, the increase or decrease of offered values for the realisation of works in relation to the moment in which the estimation of realisation costs for future projects will be made, by applying the model. In other words, by applying the revalorisation process, the changes in the prices defined on the base date in relation to the current date will be defined. Base date is the date on which the contracted price was formed (i.e., giving an offer), whereas the current date presents the date on which the revalorisation is carried out.

Revalorisation is made based on the index of general retail prices growth in the Republic of Serbia, where the % increase in the period between February 2005 and July 2012 amounted to 95.47%, which is close to the mean value of increase of 89.91%, obtained on the basis of the values of unit prices from two final offers. After the completed revalorisation, the contracted (offered) values of realised works are directly comparable; that is, they can be classified based on the total offered revalorised value for the realisation of works (Table 3).

Classification of projects according to the total value for the realisation of works can be of great importance when training/testing of formed models for estimation. For that reason, an additional input parameter was introduced, which

Table 5: Outputs from the models.

Number	Input data description	Data type	Unit of measure	Min	Max	Mean value
Output 1	Total offered cost of realisation	Numerical	RSD	883,353.01	395,427,276.11	45,705,301.56
Output 2	Total offered duration of realisation	Numerical	day	5	120	≈38

divides projects into two subsets (values of up to and over 40,000,000 RSD) (Table 4). The borderline was defined based on the number of projects whose value does not exceed 40,000,000 RSD, which is 70% of the total number of analysed projects, whereas the mean value of offered price for all the projects is also approximately similar to this value (Table 5).

According to the previously defined subject of study, two outputs from the model were planned, the total offered price for realisation and total amount of time offered for the realisation of a project.

The next step in preparing of the data base is the normalisation process. Normalisation of data presents the process of reducing of certain data to the same order of magnitude. What is achieved in this way is for the data to be analysed with the same significance when forming a prediction model, that is, to avoid neglecting of data with a smaller order of magnitude range at the very beginning. This is the main reason why the normalisation is necessary; that is, why it is essential to transform the values into the same range by moving the range borderlines. The normalisation process was carried out for the entire set of 166 analysed projects.

Before the normalisation process is applied, considering the fact that a model based on artificial intelligence will be formed, it is necessary to divide the final set of 166 projects into a set that will be used for the training of a model, as well as the one used for the testing of formed models. Defining of which data subset will be used for the training of a model and which one for its testing, is not entirely based on the random sample method. The comparative analysis was carried out of the number of projects by categories based on the offered revalorised total price as well as the offered time for realisation of all works.

When choosing the projects that belong to the training subset, particular attention was paid to the fact that the minimum and maximum values of all parameters belong to the range of this set. In addition, all groups of projects should be equally present in both sets, according to the offered value and time for realisation. Finally, the testing subset comprised 17 pseudorandomly chosen projects (with mentioned restrictions), whereas the remaining 149 projects constitute the training subset.

The most commonly used forms of data normalisation, being the simplest ones at the same time, are the min-max normalisation and Zero-Mean normalisation [61], which were applied in the conducted research.

The first step in forming of models for estimation by using ANNs relates to defining of the number of hidden layers. According to Huang and Lipmann [62] there is no need to use ANNs with more than two hidden layers, which has been confirmed by many theoretical results and a number of simulations in various engineering fields. Moreover, according to Kecman [63] it is recommendable to start the solving of a problem by using a model with one hidden layer.

By choosing the optimal number of neurons, it is necessary to avoid two extreme cases: omission of basic functions (insufficient number of hidden neurons) and overfitting (too many hidden neurons). In order to achieve proper generalisation "power" of an ANN model, it is necessary to apply the cross-validation procedure, owing it to the fact that good results during the training process do not guarantee proper generalisation "power." What is meant by generalisation is the "ability" of an ANN model to provide satisfactory results by using data which were not known to the model during the training (validation subset).

For the purpose of the cross-validation procedure within the training subset, 17 pseudorandomly chosen projects were taken, based on the same principle as within the testing subset, that is, the equal percentage share of projects in terms of value. If there is not too much difference, that is, deviation between estimated and expected values, percentage error (PE) or absolute percentage error (APE), or mean absolute percentage error (MAPE), in all three subsets (training, validation, and testing), it can be considered that this is the actual generalisation power of the formed ANN model, that is, that there is no "overfitting."

All the models for estimation of costs and duration were formed in the Statistica 12 software package, in which it is possible to define two types of ANN models, MLP (Multilayer Perceptron) and RBF (Radial Basis Function) models. According to Matignon [64], both models are used to deal with classification problems, while the MLP models are used to deal with regression problems and RBF models with clustering problems. Since the subject of the research involves the estimation of costs and duration, that is, belonging to regression problems, only the MLP ANN models were formed.

Activation function of output neurons is mainly linear when it comes to regression problems. When the activation functions of hidden neurons are concerned, the most commonly used functions are logistic unipolar and sigmoidal bipolar (hyperbolic tangent being the most commonly used one) [63]. In accordance with this recommendation for all the models, activation functions for hidden neurons logistic sigmoid and hyperbolic tangent were used, while the activation function identity was used for output neurons (Table 6).

4. Results and Discussion

Based on previously defined inputs, outputs, and defined parameters in each iteration, 10.000 ANN MLP models were formed, and one model with the smallest estimation error was chosen. The number of input and output neurons was defined by the number of inputs and outputs, whereas the number of

Table 6: Activation functions of MLP ANN models.

Function	Expression	Explanation	Range
Identity	$\mathbf{a}$	Activation of neurons is directly forwarded as output	$(-\infty, +\infty)$
Logistic sigmoid	$\frac{\mathbf{1}}{\mathbf{1}+\mathbf{e}^{-\mathbf{a}}}$	"S" curve	$(0, 1)$
Hyperbolic tangent	$\frac{\mathbf{e}^{\mathbf{a}}-\mathbf{e}^{-\mathbf{a}}}{\mathbf{e}^{\mathbf{a}}+\mathbf{e}^{-\mathbf{a}}}$	Sigmoid curve similar to logistic function, but featuring better performances because of the symmetry it has. Ideal for MLP ANN models, especially for hidden neurons	$(-1, +1)$

Table 7: ANN models (min-max).

Model	Network	Activation function hidden neurons	Activation function output neurons	MAPE training (cost) [%]	MAPE training (duration) [%]	MAPE testing (cost) [%]	MAPE testing (duration) [%]
ANN 1	MLP 12-4-2	Tanh	Identity	42.79	31.85	40.54	35.48
ANN 2	MLP 11-6-2	Logistic	Identity	41.88	31.82	26.97	30.22
ANN 3	MLP 12-6-1	Tanh	Identity	33.02	/	25.38	/
ANN 4	MLP 11-7-1	Tanh	Identity	39.16	/	26.88	/
ANN 5	MLP 12-8-1	Tanh	Identity	/	34.16	/	26.26
ANN 6	MLP 11-10-1	Logistic	Identity	/	33.29	/	35.16

Table 8: ANN models (Zero-Mean).

Model	Network	Activation function hidden neurons	Activation function output neurons	MAPE training (cost) [%]	MAPE training (duration) [%]	MAPE testing (cost) [%]	MAPE testing (duration) [%]
ANN 7	MLP 12-7-2	Logistic	Identity	52.16	30.89	37.96	34.23
ANN 8	MLP 11-8-2	Logistic	Identity	48.04	32.06	42.54	34.20
ANN 9	MLP 12-4-1	Tanh	Identity	37.49	/	20.22	/
ANN 10	MLP 11-8-1	Tanh	Identity	40.99	/	28.28	/
ANN 11	MLP 12-8-1	Tanh	Identity	/	32.32	/	37.20
ANN 12	MLP 11-5-1	Tanh	Identity	/	33.13	/	35.59

hidden neurons was limited to maximum of 10. A total of 12 ANN models were chosen, 6 of them being normalised by the min-max procedure and the remaining 6 by the Z Score procedure.

By using the ANN 1 and ANN 2 models, simultaneous estimation of costs and duration was carried out. The ANN 1 model had 12 inputs and 2 outputs, whereas the ANN 2 model was formed by using 11 inputs. Elimination of one input parameter followed the analysis of the influence of input parameters, which showed that the realisation zone (11i) has the smallest influence on the values of the output data. The same principle was applied in forming of ANN 3 and ANN 4 models for the estimation of costs only, as well as the ANN 5 and ANN 6 models for the estimation of time needed for the realisation of works.

Table 7 shows the chosen models (min-max normalisation) with defined characteristics of models and defined accuracy of estimation expressed through the MAPE.

Forming of the remaining 6 ANN models with data whose normalisation was performed by using the Zero-Mean normalisation was carried out in the same way. In this case as well the realisation zone (11i) has the smallest impact on the output values. Table 8 provides an outline of chosen models with defined characteristics of models and defined accuracy of estimation expressed through the MAPE.

The comparative analysis of presented models clearly shows that the greater accuracy of estimation is achieved by models formed based on the data prepared by the min-max normalisation procedure. The accuracy of estimation of formed models is unsatisfactory, that is, being considerably larger than the desirable ±15% for the costs of construction.

The first step in the forming of models for estimation by using the SVM as well as the ANN models relates to defining of input and output data. In the process of forming of SVM models, the used data had previously been prepared by applying the min-max normalisation, as it was proved that using it results in the greater accuracy in the case of ANN models. Moreover, only the models for separate estimation of costs and duration of construction were formed. The main reason for this lies in the fact that the greater accuracy is achieved by separate estimation, that is, by forming of separate models, which was proved on the ANN models. However, the software package Statistica 12 itself does not provide the option of simultaneous estimation of several parameters by using the

Table 9: Functions of error of SVM models.

SVM type	Error function	Minimize subject to
Type 1	$\frac{1}{2}w^T w + C\sum_{i=1}^{N}\xi_i + C\sum_{i=1}^{N}\xi^*{}_i$	$w^T\phi(x_i) + b - y_i \le \varepsilon + \xi^*{}_i$ $y_i - w^T\phi(x_i) - b_i \le \varepsilon + \xi_i$ $\xi_i, \xi^*{}_i \ge 0\ , i = 1, N$
Type 2	$\frac{1}{2}w^T w - C\left(\nu\varepsilon + \frac{1}{N}\sum_{i=1}^{N}(\xi_i + \xi^*{}_i)\right)$	$(w^T\phi(x_i) + b) - y_i \le \varepsilon + \xi^*{}_i$ $y_i - (w^T\phi(x_i) + b_i) \le \varepsilon + \xi_i$ $\xi_i, \xi^*{}_i \ge 0,\ i = 1, N,\ \varepsilon \ge 0$

Table 10: SVM models (min-max).

Model	C	ε	$\frac{1}{2\sigma^2}$	MAPE training (cost) [%]	MAPE training (duration) [%]	MAPE testing (cost) [%]	MAPE testing (duration) [%]
SVM 1	20	0.001	0.083	25.28	/	15.47	/
SVM 2	20	0.001	0.091	23.96	/	7.06	/
SVM 3	20	0.001	0.083	/	29.21	/	24.59
SVM 4	20	0.001	0.091	/	30.75	/	22.77

SVM. Within the mentioned software package, two functions of error in the forming of SVM models are offered (Table 9).

For Type 1 (epsilon-SVM regression) it is necessary to define parameter capacity (C) and epsilon (ε), insensitivity zone. At the same time, for Type 2 (nu-SVM regression) it is necessary to define parameter capacity (C) and Nu (γ). The value of parameters $\mathbf{C}$ and $\boldsymbol{\varepsilon}$ ranges between 0 and ∞, whereas the value of parameter $\boldsymbol{\gamma}$ ranges between 0 and 1. It is also necessary to choose one of the offered Kernel functions: linear, polynomial, RBF, or sigmoid. RBF kernel function presents the most frequently used kernel function for forming of SVM models:

$$\mathbf{K}\left(\mathbf{x_i}, \mathbf{x_j}\right) = \exp\left(-\frac{\mathbf{1}}{\mathbf{2\sigma^2}}\left\|\mathbf{x} - \mathbf{x_i}\right\|^2\right) \quad \boldsymbol{\sigma} - \text{width of RBF function.} \tag{1}$$

When using the RBF kernel function it is necessary to define the parameter $\boldsymbol{\gamma} = \mathbf{1/2\sigma^2}$. For the purpose of forming of the model, the function of error Type 1 was used.

A total of four SVM models were formed, with the same number of input parameters as in the case of ANN models, from the perspective of input parameters SVM 1 = ANN 3 and ANN 9, SVM 2 = ANN 4 and ANN 10, SVM 3 = ANN 5 and ANN 11, and SVM 4 = ANN 6 and ANN 12. The reason for this is the easier comparative analysis of results obtained by using the listed models. Table 10 shows characteristics of formed models with defined accuracy of estimation expressed through the MAPE.

After forming the SVM models, it is evident that they provide greater accuracy of estimation of both costs and duration of projects as well. The shown accuracy of estimation made through the MAPE is not sufficient for the choice of a model, but it is necessary to carry out the analysis of accuracy of estimation for each of the projects separately, especially those from the testing subset. The estimation error is expressed through the PE (percentage error), which is shown in Table 11 for the estimation of costs and in Table 12 for the estimation of duration of projects. Defining of the PE is of particular importance for the estimation of costs, in order to carry out the comparative analysis with the desired accuracy of ±15% for each of the projects from the testing set separately.

Errors in the estimation of duration are higher when compared to estimation of offered prices for the realisation of works, since the investor defined in the tender documentation the maximum possible duration of works, which is more than an optimistic prediction. In other words, the offered time is not the result of the estimation by the contractor, but the limitation set by the investor. For this reason, contractors adopted automatically the maximum offered duration of works.

Additionally, it can be stated that models for separate estimation of costs and duration provide a higher level of accuracy than those which carry the estimation out simultaneously, which is specifically the case with ANN models. The reason for this lies in the fact that the impact of input parameters on the output ones is not the same for the estimation of costs and duration of works.

Figure 1 shows the influence of input parameters on the output ones in the case of estimation of costs, for the ANN 3 and ANN 4 models. The input data are divided into four categories, that is, two groups and two independent pieces of input data. The first group presents inputs which relate to amounts of materials needed for the realisation of works on the roadway construction and landscaping; the second one relates to the share of works by the remaining groups of works from the bill of works, whereas the independent input data relates to the realisation zone and the category of the project.

Figure 2 Illustrates the influence of input parameters for the ANN 5 and ANN 6 models, that is, models for the estimation of duration of projects.

Based on the graphs given above, it can clearly be noticed that the second group of input data has a considerably greater influence on the estimation of project duration, diminishing the influence of the first group. Moreover, the category of the project is of approximately the same significance for the

Table 11: PE for estimation of costs, testing set.

	Expected cost [RSD]	PE for the cost for the model testing [%]					
		ANN 1	ANN 2	ANN 3	ANN 4	SVM 1	SVM 2
(1)	2.648.222,52	−102.64	50.14	7.02	−22.16	35.13	29.26
(2)	3.745.996,06	−135.49	24.81	−64.12	−6.85	10.90	2.95
(3)	4.316.450,20	−71.75	−3.35	−58.63	−4.19	3.30	−3.69
(4)	4.406.745,87	−8.84	−28.48	−26.43	43.85	−101.06	−17.16
(5)	5.894.577,64	−61.60	−56.76	−30.47	−71.95	6.58	−6.68
(6)	6.228.262,97	108.17	61.10	58.49	70.07	−0.36	11.47
(7)	7.959.531,14	−8.24	−22.17	−26.71	−45.93	−21.82	−14.67
(8)	14.402.129,26	−25.13	−10.58	12.93	27.89	−31.66	3.81
(9)	15.499.081,98	−33.01	−15.10	−25.31	−23.05	6.85	6.93
(10)	24.298.158,68	−11.78	55.89	−11.72	−5.09	−6.95	2.46
(11)	29.293.376,43	−6.23	−1.86	−2.24	−18.82	0.25	0.19
(12)	31.331.583,69	−22.66	−17.92	−9.52	−23.11	−6.58	−3.87
(13)	48.628.946,36	−12.12	−37.33	4.69	6.09	−4.72	2.68
(14)	68.428.523,13	−61.68	−25.73	−58.10	−51.68	−13.91	−6.86
(15)	74.828.211,00	8.16	25.96	7.08	4.65	7.95	4.28
(16)	121.971.479,98	6.97	11.85	26.16	30.90	2.68	1.90
(17)	267.333.894,15	−4.63	−9.51	−1.91	−0.62	−2.31	−1.21
	MAPE	*40.54*	*26.97*	*25.38*	*26.88*	*15.47*	*7.06*

Table 12: PE for estimation of duration, testing set.

	Expected duration [day]	PE for the duration of the model testing subset [%]					
		ANN 1	ANN 2	ANN 5	ANN 6	SVM 3	SVM 4
(1)	12	−26.88	−27.47	−20.84	−17.89	−29.45	−69.18
(2)	26	49.00	14.41	14.84	37.66	6.31	−2.46
(3)	20	11.24	−4.21	7.70	24.81	−4.03	−7.53
(4)	35	−0.63	1.07	9.13	−45.02	11.06	28.42
(5)	34	19.86	22.68	13.73	29.95	35.81	36.24
(6)	17	34.71	26.11	−13.14	−12.66	−5.80	0.01
(7)	17	−39.19	−27.34	−21.32	35.01	31.42	27.06
(8)	20	−86.38	−38.59	−57.30	−93.00	−83.95	−41.62
(9)	25	3.90	−14.67	−3.53	−2.19	5.42	−0.93
(10)	35	−16.14	13.57	−0.55	6.17	−28.22	−1.72
(11)	25	−61.40	−62.19	−55.17	−54.97	−17.28	−23.71
(12)	38	0.66	−14.99	0.85	−1.74	21.63	19.26
(13)	41	−124.67	−123.00	−113.63	−103.76	−66.12	−63.11
(14)	60	−51.47	−53.54	−47.83	−56.72	−23.93	−24.82
(15)	60	42.08	43.97	37.67	44.03	17.42	13.95
(16)	60	−29.36	−24.88	−17.08	−30.75	−22.26	−19.72
(17)	75	5.61	1.09	12.14	1.29	7.95	7.29
	MAPE	*35.48*	*30.22*	*26.26*	*35.16*	*24.59*	*22.77*

estimation of both costs and duration as well, whereas the realisation zone has a considerably greater impact on the estimation of duration of the project.

5. Conclusions

Based on the results presented above, a conclusion was drawn that a greater accuracy level in estimating of costs and duration of construction is achieved by using of models for separate estimation of costs and duration. The reason for this lies primarily in the different influence of input parameters on the estimation of costs in comparison with the estimation of duration of the project. By integrating them into a single model a compromise in terms of the significance of input data is made, resulting in the lower precision of estimation when it comes to ANN models.

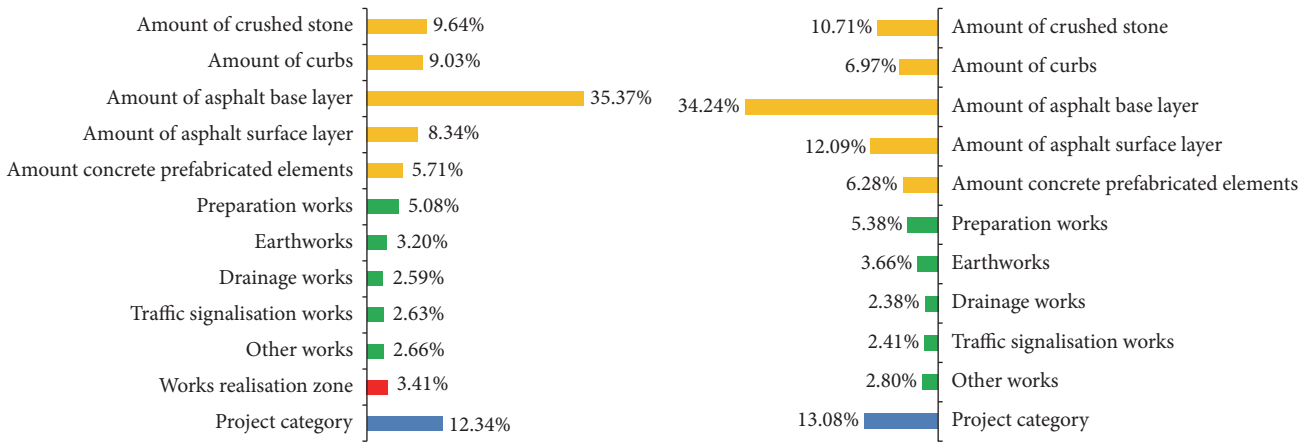

Figure 1: Analysis of sensitivity (ANN 3 and ANN 4); estimation of construction costs.

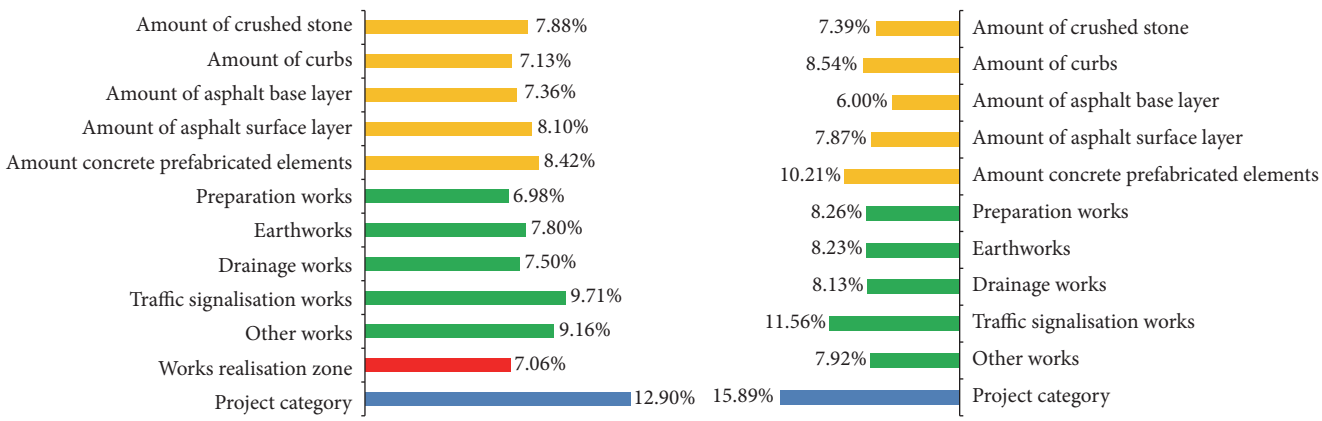

Figure 2: Analysis of sensitivity (ANN 5 and ANN 6); estimation of duration of construction.

SVM models feature a greater capacity of generalisation, providing at the same time greater accuracy of estimation, for the estimation of both costs and duration of projects as well. In both cases, the greatest accuracy of estimation is achieved by the SVM model with 11 input parameters, that is, without a more considerable influence of the project realisation zone, which implies that the investors did not pay particular attention when defining the offered price and time to whether the works will be realised within the city zone or the suburbs.

Extending of the data base in terms of the very subject of a contract, that is, the future construction object, and the introduction of parameters, such as the length of the section, the roadway width, the urban road category (boulevard, side alley, etc.), the length of cycling lanes, areas intended for parking, pedestrian lanes, and plateaus, would widely extend the possibility of application of estimation models. There is a wide range of potential parameters which can be introduced as the feature of the construction object, presenting at the same time the input data for the estimation model. In this way, the possibility of estimating the costs and duration of construction in the contracting phase not only when the bill of works is defined (query by tender), but also when the investor defines only the guidelines, that is, the conditions that the future construction object has to meet (query by functional parameters of a future object), is created. Forming of a model with functional features of a future construction object as input parameters could have a double application from both perspectives, of the investor and the contractor. From the perspective of the investor, if the accuracy of estimation similar to that of already formed models was achieved, the precision in estimation in the initial phase and defining of criteria, which the future object is to meet, would be considerably above the one required by the literature (±50%) [10].

The research was conducted for the estimation of costs and duration of realisation for "build" contracts. This approach provides an option to estimate "design-build" contracts as well; that is, the experience gained through "build" contracts can be used in future estimations of "design-build" contacts, for both the needs of the investor and the contractor as well. Application of future models largely depends on the available information at the time of estimation. For this reason, the input data should be adjusted to the available information at the given moment, for both the investor and the contractor as well.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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References

[1] J. Gunner and M. Skitmore, "Comparative analysis of pre-bid forecasting of building prices based on Singapore data," *Construction Management and Economics*, vol. 17, no. 5, pp. 635–646, 1999.

[2] N. Morrison, "The accuracy of quantity surveyors' cost estimating," *Construction Management and Economics*, vol. 2, no. 1, pp. 57–75, 1984.

[3] M. Skitmore and H. P. Lo, "A method for identifying high outliers in construction contract auctions," *Engineering, Construction and Architectural Management*, vol. 9, no. 2, pp. 90–130, 2002.

[4] M. A. Azman, Z. Abdul-Samad, and S. Ismail, "The accuracy of preliminary cost estimates in Public Works Department (PWD) of Peninsular Malaysia," *International Journal of Project Management*, vol. 31, no. 7, pp. 994–1005, 2013.

[5] A. A. Aibinu and T. Pasco, "The accuracy of pre-tender building cost estimates in Australia," *Construction Management and Economics*, vol. 26, no. 12, pp. 1257–1269, 2008.

[6] S. M. Abou Rizk, G. M. Babey, and G. Karumanasseri, "Estimating the cost of capital projects: An empirical study of accuracy levels for municipal government projects," *Canadian Journal of Civil Engineering*, vol. 29, no. 5, pp. 653–661, 2002.

[7] J. S. Shane, K. R. Molenaar, S. Anderson, and C. Schexnayder, "Construction project cost escalation factors," *Journal of Management in Engineering*, vol. 25, no. 4, pp. 221–229, 2009.

[8] M. Skitmore, "Raftery curve construction for tender price forecasts," *Construction Management and Economics*, vol. 20, no. 1, pp. 83–89, 2002.

[9] B. Ivković and Ž. Popović, Upravljanje projektima u građevinarstvu. Građevinska knjiga, Beograd, 2005.

[10] A. Ashworth, *Cost Studies of Buildings*, Pearson Education Limited, England, UK, 5th edition, 2010.

[11] M. Asif and R. M. W. Horner, *Economical Construction Design Using Simple Cost Models*, University of Dundee, 1989.

[12] R. M. Horner, K. J. McKay, and M. M. Saket, "Cost-significance in Estimating and Control, Symposium Organization in Construction," in *Proceedings of the Cost-significance in Estimating and Control, Symposium Organization in Construction*, pp. 571–585, Opatija, Croatia, 1986.

[13] H. Adeli, "Neural networks in civil engineering: 1989–2000," *Computer-Aided Civil and Infrastructure Engineering*, vol. 16, no. 2, pp. 126–142, 2001.

[14] A. M. Elazouni, I. A. Nosair, Y. A. Mohieldin, and A. G. Mohamed, "Estimating resource requirements at conceptual design stage using neural networks," *Journal of Computing in Civil Engineering*, vol. 11, no. 4, pp. 217–223, 1997.

[15] V. Albino and A. C. Garavelli, "A neural network application to subcontractor rating in construction firms," *International Journal of Project Management*, vol. 16, no. 1, pp. 9–14, 1998.

[16] A. W. T. Leung, C. M. Tam, and D. K. Liu, "Comparative study of artificial neural networks and multiple regression analysis for predicting hoisting times of tower cranes," *Building and Environment*, vol. 36, no. 4, pp. 457–467, 2001.

[17] S. Rebaño-Edwards, "Modelling perceptions of building quality-A neural network approach," *Building and Environment*, vol. 42, no. 7, pp. 2762–2777, 2007.

[18] D. Vouk, D. Malus, and I. Halkijevic, "Neural networks in economic analyses of wastewater systems," *Expert Systems with Applications*, vol. 38, no. 8, pp. 10031–10035, 2011.

[19] J.-H. Chen and S. C. Hsu, "Hybrid ANN-CBR model for disputed change orders in construction projects," *Automation in Construction*, vol. 17, no. 1, pp. 56–64, 2007.

[20] N. B. Chaphalkar, K. C. Iyer, and S. K. Patil, "Prediction of outcome of construction dispute claims using multilayer perceptron neural network model," *International Journal of Project Management*, vol. 33, no. 8, article no. 1808, pp. 1827–1835, 2015.

[21] H. P. Tserng, G.-F. Lin, L. K. Tsai, and P.-C. Chen, "An enforced support vector machine model for construction contractor default prediction," *Automation in Construction*, vol. 20, no. 8, pp. 1242–1249, 2011.

[22] K. C. Lam, E. Palaneeswaran, and C.-Y. Yu, "A support vector machine model for contractor prequalification," *Automation in Construction*, vol. 18, no. 3, pp. 321–329, 2009.

[23] M. Y. Cheng and A. F. V. Roy, "Evolutionary fuzzy decision model for cash flow prediction using time-dependent support vector machines," *International Journal of Project Management*, vol. 29, no. 1, pp. 56–65, 2011.

[24] M. Wauters and M. Vanhoucke, "Support Vector Machine Regression for project control forecasting," *Automation in Construction*, vol. 47, pp. 92–106, 2014.

[25] V. Mučenski, M. Trivunić, G. Ćirović, I. Peško, and J. Dražić, "Estimation of recycling capacity of multistorey building structures using artificial neural networks," in *Acta Polytechnica Hungarica*, vol. 10, pp. 175–192, 4 edition, 2013.

[26] S. O. Cheung, P. S. P. Wong, A. S. Y. Fung, and W. V. Coffey, "Predicting project performance through neural networks," *International Journal of Project Management*, vol. 24, no. 3, pp. 207–215, 2006.

[27] H. M. Günaydin and S. Z. Doğan, "A neural network approach for early cost estimation of structural systems of buildings," *International Journal of Project Management*, vol. 22, no. 7, pp. 595–602, 2004.

[28] M. Arafa and M. Alqedra, "Early stage cost estimation of buildings construction projects using artificial neural networks," *Journal of Artificial Intelligence Research*, vol. 4, no. 1, pp. 63–75, 2011.

[29] M. Bouabaz and M. Hamami, "A cost estimation model for repair bridges based on artificial neural network," *American Journal of Applied Sciences*, vol. 5, no. 4, pp. 334–339, 2008.

[30] D. P. Alex, M. Al Hussein, A. Bouferguene, and S. Fernando, "Artificial neural network model for cost estimation: City of edmonton's water and sewer installation services," *Journal of Construction Engineering and Management*, vol. 136, no. 7, pp. 745–756, 2010.

[31] I. Siqueira, *Neural Network-Based Cost Estimating, [Master, thesis]*, University of Montreal, Quebec, Department of Building, Civil and Environmental Engineering, Canada, 1999.

[32] S.-H. An, U.-Y. Park, K.-I. Kang, M.-Y. Cho, and H.-H. Cho, "Application of support vector machines in assessing conceptual cost estimates," *Journal of Computing in Civil Engineering*, vol. 21, no. 4, pp. 259–264, 2007.

[33] H. Adeli and M. Wu, "Regularization neural network for construction cost estimation," *Journal of Construction Engineering and Management*, vol. 124, no. 1, pp. 18–24, 1998.

[34] C. G. Wilmot and B. Mei, "Neural network modeling of highway construction costs," *Journal of Construction Engineering and Management*, vol. 131, no. 7, pp. 765–771, 2005.

[35] B. Vahdani, S. M. Mousavi, M. Mousakhani, M. Sharifi, and H. Hashemi, "A neural network modela based on support Vector machine for conceptual cost estimation in construction projects," *Journal of Optimization in Industrial Engineering*, vol. 10, p. 11, 2012.

[36] F. Kong, X.-J. Wu, and L.-Y. Cai, "A novel approach based on support vector machine to forecasting the construction project cost," in *Proceedings of the 2008 International Symposium on Computational Intelligence and Design (ISCID '08)*, pp. 21–24, China, October 2008.

[37] F. Kong, X. Wu, and L. Cai, "Application of RS-SVM in construction project cost forecasting," in *Proceedings of the 4th International Conference on Wireless Communications, Networking and Mobile Computing (WiCOM '08)*, Dalian, China, October 2008.

[38] G. Kim, J. Shin, S. Kim, and Y. Shin, "Comparison of School Building Construction Costs Estimation Methods Using Regression Analysis, Neural Network, and Support Vector Machine," *Journal of Building Construction and Planning Research*, vol. 01, no. 01, pp. 1–7, 2013.

[39] G. H. Kim, S. H. An, and K. I. Kang, "Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning," *Building and Environment*, vol. 39, no. 10, pp. 1235–1242, 2004.

[40] R. Sonmez, "Conceptual cost estimation of building projects with regression analysis and neural networks," *Canadian Journal of Civil Engineering*, vol. 31, no. 4, pp. 677–683, 2004.

[41] G. H. Kim, D. S. Seo, and K. I. Kang, "Hybrid models of neural networks and genetic algorithms for predicting preliminary cost estimates," *Journal of Computing in Civil Engineering*, vol. 19, no. 2, pp. 208–211, 2005.

[42] W. F. Feng, W. J. Zhu, and Y. G. Zhou, "The application of genetic algorithm and neural network in construction cost estimate," in *Proceedings of the Third International Symposium on Eletronic Commerce and Security Workshop (ISECS '10)*, pp. 151–155, Guangzhou, China, 2010.

[43] M. Y. Cheng and C. J. Huang, "Construction Conceptual Cost Estimates Using Evolutionary Fuzzy Neural Inference Model," in *Proceedings of the 20th International Symposium on Automation and Robotics in Construction*, pp. 595–600, Eindhoven, The Netherlands, September 2003.

[44] M.-Y. Cheng, H.-C. Tsai, and E. Sudjono, "Conceptual cost estimates using evolutionary fuzzy hybrid neural network for projects in construction industry," *Expert Systems with Applications*, vol. 37, no. 6, pp. 4224–4231, 2010.

[45] M. Cheng and Y. Wu, "Construction Conceptual Cost Estimates Using Support Vector Machine," in *Proceedings of the 22nd International Symposium on Automation and Robotics in Construction*, pp. 1–5, Ferrara, Italy, September 2005.

[46] S. G. Deng and T. H. Yeh, "Using least squares support vector machine to the product cost estimation," vol. 25, no. 1, pp. 1–16, 2011.

[47] M. Y. Cheng, H. S. Peng, Y. W. Wu, and T. L. Chen, "Estimate at completion for construction projects using evolutionary support vector machine inference model," *Automation in Construction*, vol. 19, no. 5, pp. 619–629, 2010.

[48] X.-Z. Wang, X.-C. Duan, and J.-Y. Liu, "Application of neural network in the cost estimation of highway engineering," *Journal of Computers*, vol. 5, no. 11, pp. 1762–1766, 2010.

[49] H. Al-Tabtabai, A. P. Alex, and M. Tantash, "Preliminary cost estimation of highway construction using neural networks," *Cost Engineering*, vol. 41, no. 3, pp. 19–24, 1999.

[50] T. Hegazy and A. Ayed, "Neural network model for parametric cost estimation of highway projects," *Journal of Construction Engineering and Management*, vol. 124, no. 3, pp. 210–218, 1998.

[51] J. Sodikov, "Cost estimation of highway projects in developing countries: artificial neural network approach," *Journal of the Eastern Asia Society for Transportation Studies*, vol. 6, pp. 1036–1047, 2005.

[52] N. I. El-Sawahli, "Support vector machine cost estimation model for road projects," *Journal of Civil Engineering and Architecture*, vol. 9, pp. 1115–1125, 2015.

[53] A. Attal, *Development of neural network models for prediction of highway construction cost and project duration [Master, thesis]*, Department of Civil Engineering and the Russ College of Engineering and Technology, Ohio University, Ohio, Ohio, USA, 2010.

[54] S. Bhokha and S. O. Ogunlana, "Application of artificial neural network to forecast construction duration of buildings at the predesign stage," *Engineering, Construction and Architectural Management*, vol. 6, no. 2, pp. 133–144, 1999.

[55] B. Hola and K. Schabowicz, "Estimation of earthworks execution time cost by means of artificial neural networks," *Automation in Construction*, vol. 19, no. 5, pp. 570–579, 2010.

[56] Y.-R. Wang, C.-Y. Yu, and H.-H. Chan, "Predicting construction cost and schedule success using artificial neural networks ensemble and support vector machines classification models," *International Journal of Project Management*, vol. 30, no. 4, pp. 470–478, 2012.

[57] I. Peško, G. Ćirović, V. Mučenski, and Ž. Tepić, "Analysis and preparation of date in neural networks calculation stage for the purpose of creating business proposals," in *Proceedings of the 10th International Conference Organization, Technology and Management in Construction, Book of Abstracts*, p. 57, Šibenik, Croatia, September 2011.

[58] I. Peško, M. Trivunić, G. Ćirović, and V. Mučenski, "A preliminary estimate of time and cost in urban road construction using neural networks," *Tehnički vjesnik*, vol. 3, no. 20, pp. 563–570, 2013.

[59] R. D. Stewart, R. M. Wyskida, and J. D. Johannes, *Cost Estimator's Reference Manual*, John Wiley & Sons, USA, 1995.

[60] D. S. Remer and H. R. Buchanan, "Estimating the cost for doing a cost estimate," *International Journal of Production Economics*, vol. 66, no. 2, pp. 101–104, 2000.

[61] F. J. M. Lopez, S. M. Puertas, and J. A. T. Arriaza, "Training of support vector machine with the use of multivariate normalization," *Applied Soft Computing*, vol. 24, pp. 1105–1111, 2014.

[62] W. Y. Huang and R. P. Lipmann, *Neural Net and Traditional Classifiers u Neural Information Processing Systems*, D. Z. Anderson, Ed., American Institute of Physics, New York, NY, USA, 1988.

[63] V. Kecman, *Learning and Soft Computing, Support Vector Machines, Neural Networks and Fuzzy Logic Models*, Massachusetts Institute of Technology (MIT), Massachusetts, Mass, USA, 2001.

[64] R. Matignon, Neural Networks Modeling using SAS Enterprise MIner, ISBN: 1-4184-2341-6, 2005.