Hindawi
Complexity
Volume 2018, Article ID 5160417, 10 pages
https://doi.org/10.1155/2018/5160417

Research Article

Urban Road Infrastructure Maintenance Planning with Application of Neural Networks

Ivan Marović,[1] **Ivica Androjić**,[1] **Nikša Jajac**,[2] **and Tomáš Hanák**[3]

[1]*Faculty of Civil Engineering, University of Rijeka, Radmile Matejčić 3, 51000 Rijeka, Croatia*
[2]*Faculty of Civil Engineering, Architecture and Geodesy, University of Split, Matice hrvatske 15, 21000 Split, Croatia*
[3]*Faculty of Civil Engineering, Brno University of Technology, Veveri 95, 602 00 Brno, Czech Republic*

Correspondence should be addressed to Tomáš Hanák; hanak.t@fce.vutbr.cz

Received 23 February 2018; Revised 11 April 2018; Accepted 12 April 2018; Published 29 May 2018

Academic Editor: Lucia Valentina Gambuzza

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 multi-objective 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

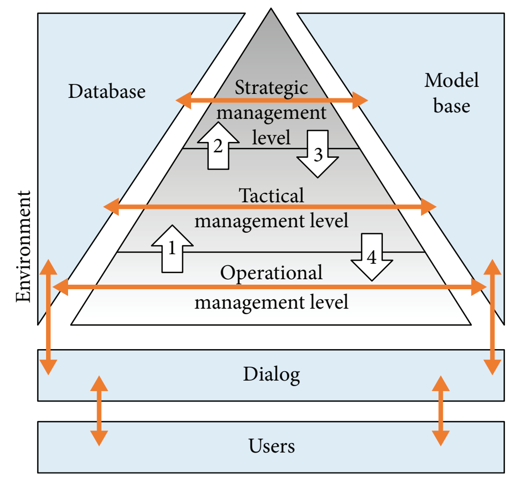

Figure 1: Structure of the decision support concept for urban road infrastructure management.

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://pavement-science.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.

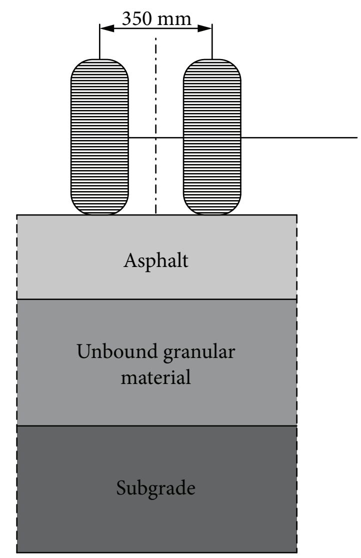

Figure 2: Cross section of the observed pavement structure.

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

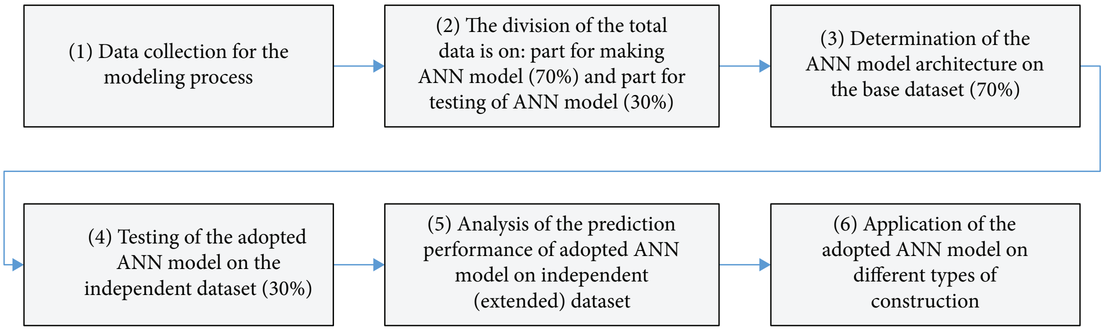

Figure 3: Diagram of the research timeline.

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, $p = 0.45$

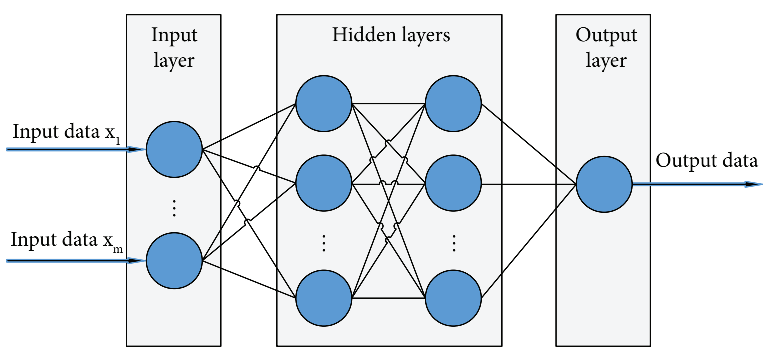

Figure 4: Configuration of the selected artificial neural network.

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

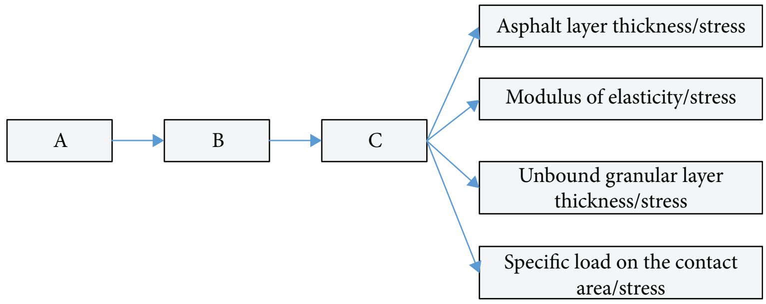

Figure 5: Test cases.

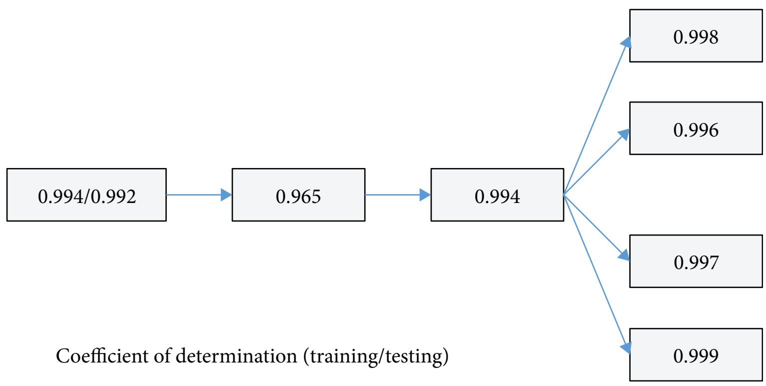

Figure 6: Test results.

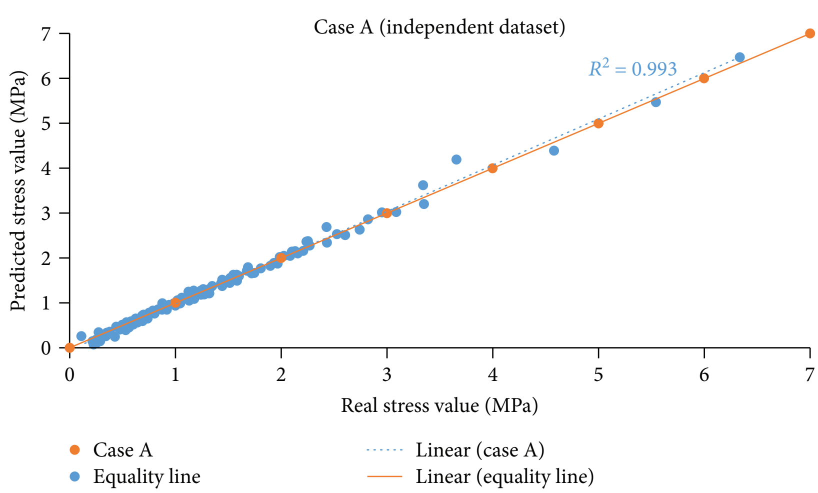

Figure 7: Results—case A.

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

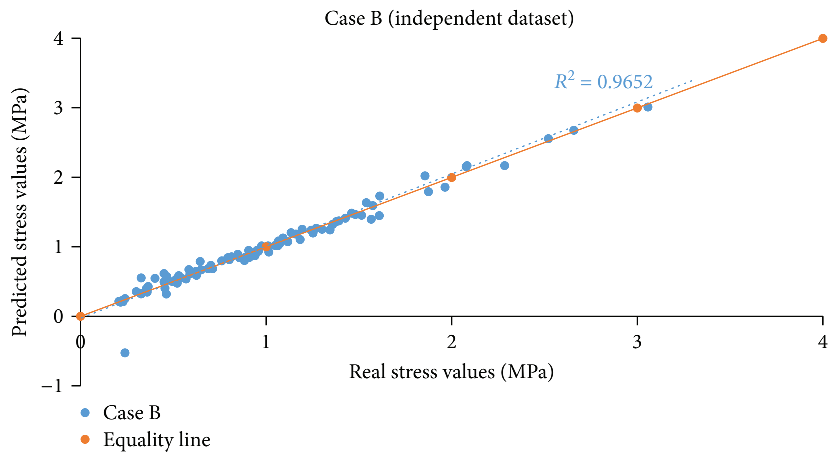

Figure 8: Results—case B.

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.

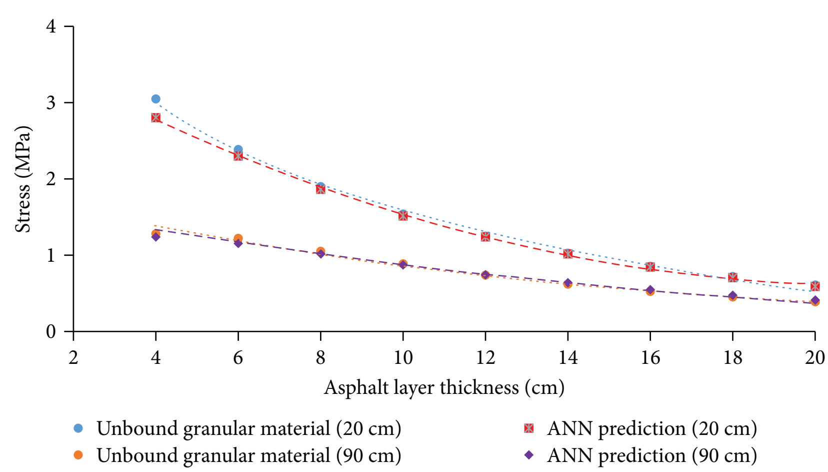

Figure 9: Results—case C1.

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.

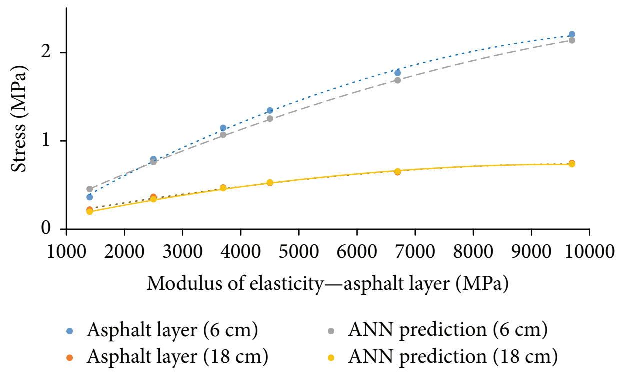

FIGURE 10: Results—case C2.

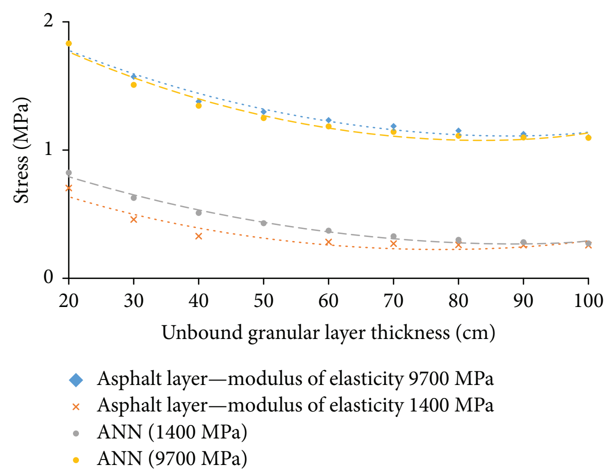

FIGURE 11: Results—case C3.

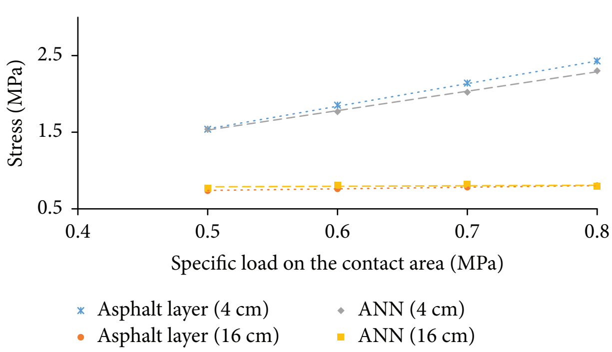

FIGURE 12: Results—case C4.

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.