Primljen/Received: 14.1.2014.
Ispravljen/Corrected: 17.2.2017.
Prihvaćen/Accepted: 25.4.2017.
Dostupno online/Available online: 10.10.2017.

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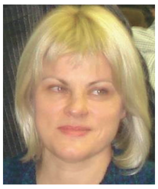

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Subject review

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Estimating investment value in railway lines reconstruction process

A prognostic model for estimating investment value of reconstruction of railway lines using artificial neural networks is presented in the paper. The aim of the model is to improve the efficiency and effectiveness of decision making as related to investment in rail infrastructure projects. The model development process is presented and illustrated with an appropriate example, which points to the possibility of using the model for making a rough and rapid assessment of the investment value of railway-lines reconstruction, with a reliability of 80-85% when some input parameters are unknown.

Key words:
railway infrastructure, investment value, reconstruction, artificial neural networks

Pregledni rad

Ljiljana Milić Marković, Ljubo Marković, Goran Ćirović, Dragan Mihajlović

Procjena investicijske vrijednosti u procesu rekonstrukcije željezničkih pruga

U radu je prikazan prognostički model za procjenu investicijskih vrijednosti rekonstrukcije željezničkih pruga izrađen primjenom umjetnih neuronskih mreža. Cilj izrade modela je poboljšanje efikasnosti i efektivnosti donošenja odluka o ulaganju u projekte željezničke infrastrukture. Prikazan je proces izrade modela i dan je odgovarajući primjer kojim se upućuje na mogućnost primjene modela za eventualne grube i brze procjene investicijskih vrijednosti za rekonstrukciju željezničkih pruga s pouzdanošću od 80 do 85 % kada nisu poznati svi ulazni parametri.

Ključne riječi:
željeznička infrastruktura, investicijska vrijednost, rekonstrukcija, umjetne neuronske mreže

Übersichtsarbeit

Ljiljana Milić Marković, Ljubo Marković, Goran Ćirović, Dragan Mihajlović

Einschätzung des Investitionswerts bei der Rekonstruktion von Eisenbahnstrecken

In der Arbeit wird das Prognosemodell für die Bewertung des Investitionswerts der Rekonstruktion von Eisenbahnstrecken dargestellt, entwickelt anhand eines künstlichen neuronalen Netzwerks. Ziel der Modellentwicklung ist die Steigerung der Effizienz und Effektivität der Entscheidungen über Investitionen in Eisenbahninfrastrukturprojekte. Das Verfahren der Modellentwicklung wird näher dargestellt. Anhand eines Beispiels wird auf die Einsatzmöglichkeiten des Modells bei einer groben und schnellen Bewertung des Investitionswerts für die Rekonstruktion von Eisenbahnstrecken hingewiesen, mit einer Zuverlässigkeit von 80 bis 85 % wenn nicht alle Eingangsparameter bekannt sind.

Schlüsselwörter:
Eisenbahninfrastruktur, Investitionswert, Rekonstruktion, künstliche neuronale Netzwerke

1. Introduction

In accordance with the global strategy for rational redistribution of traffic, and in line with the plans presented by neighbouring countries and Europe as a whole, the Republic of Serbia has signed the following international agreements:

- European Agreement on Main International Railway Lines [1],
- European Agreement on Important International Combined Transport Lines and Related Installations, [2],
- Agreement on the Establishment of a High Performance Railway Network in South East Europe [3].

The principal aim of signing these agreements was to achieve, through adequate measures and in a reasonable time period, such an advanced level of infrastructure in the Serbian rail network that will enable, assisted by modernisation of rail vehicles, achievement of high technical interoperability standards [4], so that Serbian network can accommodate other operators and enable competition. In addition, Serbian Railways plc will increasingly attract passengers and goods through such high level of services, in line with its public and commercial functions.
The existing railway network in Serbia was built mainly in the second half of the 19th century and during the 20th century, with track elements fulfilling the requirements of the time. Over the past 30 years, not enough has been invested in this network, which is principally due to general economic sluggishness, poor organization, and the lack of funding even for basic maintenance and repair of railway lines. Thus, no more than approximately 36 km of track lines are repaired annually (instead of the necessary 190 km). Over the past decade, and even since 2002, an average annual investment in railway infrastructure amounted to 16.5 million euros, mainly from loans (e.g. in the Republic of Croatia, the annual investment for the same period amounted to 113 million euros) [5]. As a result, we are currently faced with the situation in which speeds in excess of 100 km/h are allowed on 3.2 % of track lines only, while a maximum speed limit of 60 km/h is applied on the majority of the network (about 50 %). On some lines, there are sections where the speed is limited to 20 km/h or less. The European standard for the maximum permissible load capacity of 225 kN/axle is met by 44 % of the lines. Out of the total rail network length (3,809 km), there are 1,247 km of electrified track lines (32.7 %), and 276 km (7 %) of double track lines [6]. Today, Serbia is ranked 110 out of 132 countries for the quality of its railway infrastructure [5].
trategy for the development of rail, road, water, air and intermodal transport in the Republic of Serbia 2008-2015 was adopted in 2008. [6]. The Strategy identified the situation in these areas of transport, established the concept for development of infrastructure and transport, defined long-term transport system development goals, and adopted an action plan for their implementation [6]. According to this Strategy, rail transport development phases are: restoration, reconstruction and modernization, and construction. In the reconstruction phase, the goal is to harmonize characteristics of rail transport infrastructure in the Republic of Serbia with those prevailing in the European Union member states. This phase is funded from loans provided by international financial institutions, from European Union funds, and from national sources. According to estimates given in the Strategy, around 3.9 billion euros will have to be allocated for this phase over the next decade [6].
Therefore, reconstruction of railway lines is a highly topical problem at the current level of development of the Serbian rail network. Under conditions of economic crisis, the reconstruction of Serbian railway network, aimed at bringing it to a higher level of quality and functionality, is a priority over new construction.
The implementation of any reconstruction project is highly dependent on investment policies. Principal challenges in relation to investment in railway infrastructure are related to making proper investment decisions.
In order to successfully reconstruct railway lines in Serbia in accordance with what is needed and in the light of the current financial possibilities, and to achieve maximum effects with each investment project, it is necessary to adopt a systemic approach to investment decision making, recognizing the fact that the "highest price is the price resulting from poor decision-making".

2. Assessment of railway lines reconstruction investments using neural networks

Making decisions related to reconstruction work on railway lines is a very complex process. Decisions on work needed are based on the information from various sources, which objectively defines the condition of the railway line in the light of requirements regarding its wider and narrow area of influence. Based on the available and collected information on the existing condition of the railway, appropriate analyses are made in order to:

- identify and assess the existing condition of the rail network,
- make an assessment of future changes,
- Identify current and future demands on the rail network,
- Predict impact of planned works on the current and/or future condition,
- Determine funding needed to fulfil current requirements,
- Determine funding needed to implement the planned reconstruction program.

The quality of the above analyses directly depends on the information on rail lines as stored in the rail network database, which is a basic and indispensable link for successful problem solving.
Development of artificial intelligence, as a means of support to the decision-making process in railway reconstruction works, has also resulted in generation of methods based on various expert system techniques. An expert system is an intelligent computer program that uses knowledge and inference procedures for solving problems. Expert systems simulate human expertise and can solve problems that do not have algorithmic solutions [7].

One such system is ECOTRACK. It is a compilation of most of the existing systems and, as such, it contains the highest quality solutions from these systems. What makes ECOTRACK special is its very detailed set of rules for making decisions regarding the need for maintenance and reconstruction. These rules are based on decay parameter models. Many prominent experts from most European rail administrations took part in the definition of these rules. The ECOTRACK system is flexible and open for new experience, i.e. it allows addition, change and elimination of rules, but at the discretion of railway administrations [7]. The functional architecture of ECOTRACK is made of five levels. Each level represents a planning activity that includes several detailed functions [7]:

- Level 1: Initial diagnostic – the system uses a database and knowledge base to carry out a preliminary diagnosis of each permanent-way section (geometry, permanent way structure, ballast, and infrastructure). Basic works are defined for each section (geometry, rails, sleepers) and additional information is collected in connection with the state of the track and stored in the database.
- Level 2: Detailed diagnostic – the information collected is used, and decision-making rules for level 2 are applied in order to define the basic works. The user can check and the decisions made by the system.
- Level 3: Harmonisation – a set of rules is used to ensure automatic harmonisation of works, based on the list of basic works. The harmonisation can be: spatial (between two railway sections) and time-related (basic works can be combined over a time period).
- Level 4: Optimization of resources – individual prices of works are entered into the plan and total costs are analysed. The maintenance and repair plans can be changed so as to optimize them at an economic level (cost reduction).
- Level 5: Overall network management – support to the overall network maintenance by means of: statistical analysis, assessment of effects of individual permanent way components and assessment of work methods, simulation of various maintenance policies ("what if"), and simulation of limited availability of resources.

In addition to traditional methods for determining funding needed to implement a reconstruction program [8], the development of the programming concept known as soft computing has enabled the use of artificial intelligence that simulates natural processes – artificial neural networks [9].

2.1. Artificial neural networks

Artificial neural networks are defined as physical cellular systems that can learn, memorize and use experimental knowledge [10]. They are based on an analogy with the nervous system of a living being. The analogy is based on two aspects [11]:

- Knowledge that enters the neural network from the surrounding environment is used for training the neural network,
- The connections between neurons, known as synapses, are used for accumulating knowledge.

In his study, H. Adeli [12] placed emphasis on the possibility of using artificial neural networks for estimating the investment value of construction works. To improve the efficiency and effectiveness of decision-making related to investment in rail infrastructure projects, a prognostic model for estimating the value of investment in the reconstruction of railways, based on artificial neural networks, is presented below.

2.1.1. Prognostic model

Nineteen completed rail reconstruction projects were used as a basis for making a prognostic model aimed at estimating investment value for reconstruction of railway lines using neural networks [13]. For data confidentiality reasons, the names of these projects (rail sections) are indicated numerically.

The basic information about the lines on which reconstruction works were carried out was collected from previous projects (length of tracks, track structures, etc.) and using infrastructure condition databases formed at the level of rail infrastructure management companies. The databases were formed from data gained by monitoring and measurement (EM-80 L track recording car, *Plasser & Theurer* [14]). Based on these data, which were transformed into parameters for condition measurements and grouped into quality indexes, a technical analysis was carried out to determine the existing characteristics of the track (geometric condition, condition of permanent way - tracks, sleepers, etc., ballast and infrastructure) and specific railways and/or rail sections were chosen as appropriate for reconstruction works. A list of basic works was also made. The total costs of reconstruction work on each rail section were calculated on the basis of the reconstruction work planned, while the prices were defined by the user.

The condition of train station and the extent of work required were estimated, in form of fit-for-investment rating, using the existing condition assessment model. The condition / investment requirement was categorised as follows:

- 4*: excellent condition (intervention not necessary),
- 3*: small-scale interventions (roof cover replacement, façade and interior wall painting, repair of sanitary facilities),
- 2*: medium-scale interventions (repair and replacement of waterproofing, roof covering repair and replacement, replacement of exterior and interior woodwork, partial replacement of interior installations, interior improvement work),
- 1*: comprehensive interventions (intervention on structural elements of the building, moisture treatment, complete replacement of interior installations, renovation of public and sanitary facilities, replacement of roof covering, replacement of exterior and interior woodwork),
- R – demolition (when the cost of interventions needed to return the existing structure to its initial condition is close, equal to or greater than the cost of building a new structure).

The total train station reconstruction cost was calculated on the basis of the amount of work planned for the reconstruction project, while the prices were defined by the user.

Control parameters for assessing railway condition after completion of reconstruction work were measured using a track recording car. The data obtained were analysed and compared with the corresponding criteria and tolerance thresholds as specified in the reconstruction project. Based on the results of these measurements and their analysis according to behaviour and decay models, decisions were made on necessary maintenance measures and on the time of their implementation. Financial indicators relating to initially agreed prices were obtained from the corresponding contracts and annexes to such contracts, while the final cost of reconstruction work was obtained from payment certificates and the final calculation of cost incurred.

The structure of the data collected and analysed for one of the railway lines planned for reconstruction (Line 7) is provided in Tables 1, 2, 3, and 4.

Table 1. Data on basic elements of the track – track section

Railway line no. 7	
Length of the rail section	220,49 km
Length of the rail section passing through a station	26,90 km
Length of the rail section being reconstructed	110,10 km
Length of the newly constructed rail section	110,09 km
State of the electrical power infrastructure in the corridor	UNSATISFACTORY in terms of reliability, availability, maintainability and safety

Table 2. Data relating to the type and length of structures on the track – track section

Structures on railway line no. 7	**Construction cost** (EUR)
Concrete bridges, L = 1704 m	15.050.900
Steel bridges, L = 2136 m	61.147.000
Viaducts, L = 970 m	22.657.520
Galleries, L = 120 m	1.544.000
Underpasses, L = 157 m	3.274.400
Overpasses, L = 5385 m	69.388.800
Double-track tunnels, L = 10230 m	127.147.350
TOTAL:	300.209.970

Table 4. Data on engineering/geological and geotechnical conditions of the terrain

Engineering/geological and geotechnical conditions for the reconstruction of railway line no. 7	
Favourable terrain	141,76 km
Conditionally favourable terrain	77,55 km
Unfavourable terrain	1,18 km

Because of a large number of input parameters, the prognostic model development process was divided into two parts.

In the first part of the process, the input parameters were based on the data related to the number of tracks on the railway, the length of the railway/rail section passing through a station, the length of the newly constructed rail section, the length of the

Table 3. Evaluation of the state of existing architectural structures at stations

Structures at stations on railway line no. 7	**Investment rating**	**Cost of intervention on the given structures** (EUR)	**TOTAL** (EUR)
Train station no.1	2*	961 900	19.784.500
Train station no. 2	2*	875.040	
Train station no. 3	2*	759.970	
Train station no. 4	1*	1.726.200	
Train station no. 5	1*	2.936.720	
Train station no. 6	2*	449.490	
Train station no. 7	2*	564.550	
Train station no. 8	2*	470.090	
Train station no. 9	1*	6.097.530	
Train station no. 10	2*	445.120	
Train station no. 11	2*	391.920	
Train station no. 12	3*	179.560	
Train station no. 13	2*	1.411.360	
Train station no. 14	3*	189.560	
Train station no. 15	2*	360.440	
Train station no. 16	3*	184.560	
Train station no. 17	2*	358.270	
Train station no.18	2*	1.422.220	

Table 5. Input data for the first part of the process

Number of railway/ rail section	Length of railway/ rail section [km]	Single-track/ double-track railway/rail section	Length of railway/ rail section [%]			Length of railway/ rail section [%] which passes through geologically			State of the electric power plants (score*)
			which passes through a station	newly constructed	being reconstructed	favourable terrain	conditionally favourable terrain	conditionally unfavourable terrain	
	2	3	4	5	6	7	8	9	10
1	4.6	1	6.30	0	100	78.26	21.74	0	0
2	20.75	1	0.0	100	0	49.88	50.12	0	0
3	21.97	1	0.0	100	0	47.11	52.89	0	0
4	10.22	2	0.0	100	0	8.90	88.45	3.62	3
5	6.8	2	14.27	33.24	65.44	13.24	86.77	0	3
6	94	2	14.23	76.17	23.83	69.15	24.47	6.38	0
7	220.49	2	12.20	49.93	49.93	64.29	35.17	0.54	3
8	155.56	1	12.75	0	100	71.33	27.39	1.31	3
9	12	2	0.0	100	0	13.67	86.33	0	1
10	41.55	2	10.76	38.63	61.37	66.55	0	33.45	3
11	149.16	2	16.51	71.27	28.73	55.82	41.43	2.75	3
12	32.55	1	5.6	0	100	61.91	38.10	0	3
13	148.47	2	17.0	20.0	100	20.0	70.0	6.0	2
14	100.92	2	16.0	0	100	40.0	50.0	14.75	2
15	17.38	1	7.54	0	100	31.0	70.0	0	0
16	76.07	2	12.0	50.0	50.0	100	0	0	3

**(0 - rail not electrified, 1 - satisfactory, 2 - partly satisfactory, 3 - unsatisfactory in terms of reliability, availability, maintainability and safety)*

Table 6. Data on the length of structures along the railway (rail section) route

Number of railway/ rail section	Length of concrete bridges [%]	Length of steel bridges [%]	Length of underpasses [%]	Length of overpasses [%]	Length of galleries/ retaining walls [%]	Length of viaducts [%]	Length of single-track tunnel [%]	Length of single-track tunnel [%]	Number of structures with investment rating *	Number of structures with investment rating **	Number of structures with investment rating ***	Number of structures with investment rating ****
	1	2	3	4	5	6	7	8	9	10	11	12
1	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0
4	0	3.16	0.41	0.70	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0
6	1.70	0	0.14	1.72	0	0	2.47	0	5	2	3	1
7	0.77	0.97	0.07	2.44	5.40	0.44	0	4.64	3	12	3	0
8	0.26	0.80	0.11	3.18	2.25	0	0.68	0	2	12	3	2
9	0	1.00	0	0	0	0	0	0	0	0	0	0
10	0.093	0	0.25	0.20	52.0	12.86	5.39	0	0	4	0	0
11	4.51	0	0.03	1.35	7.0	0	1.67	0	0	5	2	1
12	0	0	0	0	0	0	0	0	0	0	0	0
13	0.21	0.50	0.06	0.06	0	1.70	0	1.20	0	16	0	2
14	0.04	0	0.07	4.00	0	0	0	0	1	4	1	0
15	0	0	0	0	0	0	0	0	1	0	0	0
16	0.90	0.70	0.10	3.00	0	1.00	5.00	5.00	1	4	1	1

rail section under reconstruction, the engineering and geological characteristics of the terrain through which the railway passes, and the condition of the electric power infrastructure in the railway corridor (Table 5). In the second part, the input parameters used were the data related to the length of structures along the railway/rail section and the number of architectural structures in stations with their investment value (Table 6).

Output parameters are the investment value for groups of works and the total investment cost for reconstruction of the railway/railway section.

2.1.2. Establishment of network architecture

In the process of forming the neural network architecture, it was concluded based on experience and available literature that the best results are offered by networks with a back propagation algorithm [15, 16]. The type of network was not varied since it has been shown that these networks have an optimum performance for prediction problems [17-19].

The process of finding an optimum neural network structure is based on the testing of different structures using the same data set. The testing involves varying the number of layers and number of neurons in the network. The process of determining the quality of the network structure, after the network training process, is based on determining the size of error in output results. The Levenberg-Marquardt algorithm [20] was used in the phase of finding an optimum neural network structure. It was established that, due to a small number of samples, a network of 3 layers (1 hidden) offers the best results for the given combination of input data. Choosing a network with one hidden layer reduces the possibility of over-fitting. An optimal number of 15 neurons was determined for the middle layer by varying the number of neurons, on the basis of the smallest error at the output. The hyperbolic *tangent sigmoid transfer* function was used for this network within the hidden layers, except for neurons in the output layers, where the *linear transfer* function was used. When solving the problem of prediction, input variables were grouped based on experience, without losing the quality of the input information. Because of the small sample size, no analysis of key components was carried out (PCA) so as to determine linear dependence between input parameters. The architecture of the prognostic model is shown in Figure 1.

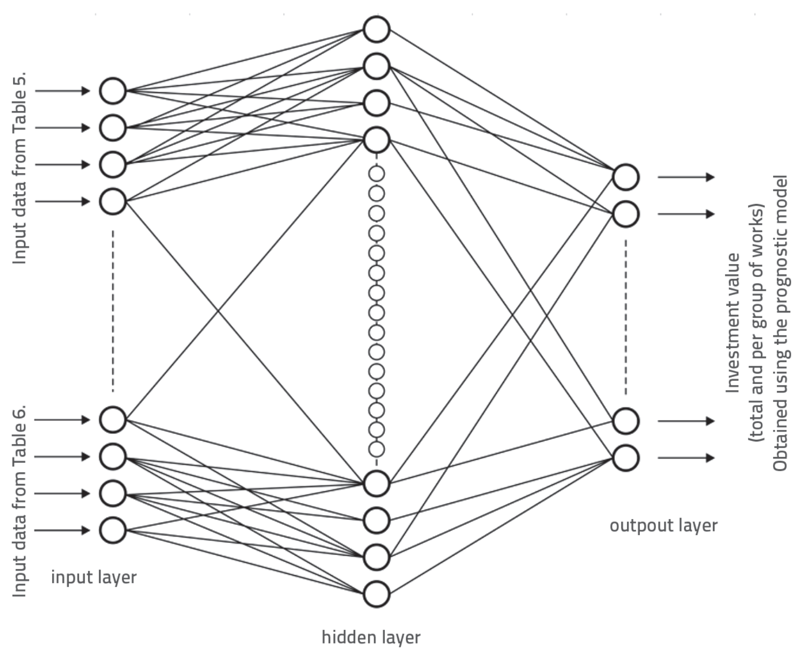

Figure 1. Network architecture of prognostic model

2.1.3. Discussion of results

A database of nineteen completed projects was formed while researching the applicability of artificial neural networks for predicting investment value of railway line reconstruction. The database contains information on the works planned for the reconstruction project: technical information (obtained from previous projects and analyses of the existing characteristics of tracks – based on measurement and monitoring results) and the data on the planned investment value of works for each section of the line being reconstructed.

Neural networks were applied to the given problem using the Matlab R2007b software package. Sixteen projects were used for training the network, and the remaining three projects were used to check prognostic models. The input mostly included condition-related parameters obtained from analysis of the existing characteristics of the lines, while investment values (total and for groups of works) were used as the output. A three-layered neural network with back-propagation was selected for training. At the beginning of the training process, there was a big difference between the prognostic value and the planned project value. In cases where large differences occurred, the weight coefficients were adjusted based on recommendations from other published research [21]. After completion of the training, the results generated by the network were more accurate. Finally, to check the quality and accuracy of the network, a control of the prognostic model was carried out.

Control of the prognostic model was performed on the set that was not used for training (railway/rail sections A, B, and C). The deviation (error) between the planned and prognostic values was used for the analysis of results. Deviations of predicted investment values, obtained using the prognostic model of investment values for the reconstruction project, are shown in Table 7. Lines 1 - 12 (Table 7) show deviation of the investment value per groups of works according to the prognostic model, as related to the

Table 7. Deviation (error) of the prognostic model for investment values, in %

No. of railway	Group of works	Deviation (error) of the prognostic model for investment values [%]			Average deviation
		Railway A	Railway B	Railway C	
1	Preliminary works	54.21	-6.60	-3.13	14.83
2	Earth works	-3.18	5.32	3.44	1.86
3	superstructure	1.67	-3.72	-0.20	-0.75
4	Hydrotechnical works	5.91	-4.62	15.56	5.62
5	Structures along the rail route	0.12	-0.30	-10.94	-3.71
6	Railway equipment	0.29	1.76	13.65	5.23
7	Works on electrical substations	8.15	1.09	8.67	5.97
8	SS substations and equipment	4.64	1.04	4.72	3.47
9	TT substations and equipment	5.33	-0.70	11.98	5.54
10	Roads along the railway route, road crossings and station squares	0.07	0.78	14.33	5.06
11	Architectural structures	0.00	-0.05	4.07	1.34
12	Other works	7.42	0.09	17.87	8.46
13	Total	1.38	-0.46	-2.20	-0.43

investment value per groups of works according to the project, expressed as a percentage. Line 13 shows deviation of the total investment value for the reconstruction and modernization of railways/rail sections according to the prognostic model, as compared to the total investment value for the project as a percentage.

Negative values in the table indicate that the projected investment value of the works was less than the actual investment value of the project.

By analysing the data presented in Table 7, it was concluded that the deviation of the prognostic model from the values obtained in the project for the total investment in reconstruction and modernization of railways ranges from -2.20 % (project C) to 1.38 % (project A). The average value of deviation of the prognostic model from the investment value given in the project is -0.43 %.

A large deviation of the prognostic model from the values obtained in the project appeared in the section for preliminary works (54.21 %) for project A. This is due to the fact that the data used for training anticipated significant costs for preliminary works (clearing the terrain), while in fact the reconstruction works for project A were carried out on the already prepared railway land.

Other large deviations of the prognostic model (15.56 %) from the actual project values were noted for hydrotechnical works in project C. In this case, significant deviations occurred as there are no complex climatic, hydrological and hydrographical conditions in the project C corridor.

For project C significant deviations of the prognostic model from the investment values obtained in the project also occurred for groups of works for roads along the railway route, road crossings and station squares (14.33 %) and other works (17.87 %).

The reason for the 14.33 % deviation of the prognostic model compared to the project value for railway C for works on roads along the railway route, road crossings and station squares was that the project had anticipated for all road and rail crossings to be grade separated and for the majority of stations to keep their original location with their already existing station squares and access roads.

A deviation of 17.87 % for other works (works related to environmental protection) for railway C occurred because technical measures for environmental protection were not foreseen for this project.

3. Conclusion

The existing railway network in Serbia, built in the second half of the nineteenth century and during the twentieth century, is characterised by technologically obsolete equipment and poor quality of maintenance. This has resulted in low train speeds, irregular network traffic, and a low level of service and safety. Due to the lack of financial resources and economic crisis, it is now imperative to reconstruct the railway network in Serbia so as to increase its quality and functionality. This reconstruction is currently considered a priority over new construction. The estimation of investment value is an important part in the process of planning reconstruction of railway lines, as it is a basis for making decisions about further investments in railway infrastructure. The task of decision makers is facilitated by currently available systems that facilitate the decision making process and enable estimation of technical and economic effects of reconstruction work. One such system, ECOTRACK, contains a highly detailed set of decision-making rules as related to maintenance and reconstruction activities. These rules are based on decay parameter models and are a compilation of rules that are applied at different railways in Europe.

In addition to the above mentioned systems, various modern operation research methods can also be used for estimating the investment value. The development of the programming and computation concept called "soft computing" has enabled the use of artificial neural networks. Therefore, a research on the use of artificial neural networks for estimating investment values relating to railway reconstruction was conducted in this paper.

The analysis and establishment of an optimum network for prediction of reconstruction activities, based on the database containing information from nineteen already realised reconstruction projects, is also presented. It was concluded that, for the database under study, the best investment prediction results are offered by a network featuring back error propagation with three layers, as combined with the Levenberg – Marquardt training algorithm. This prognostic model shows that neural networks can be used for estimating investment value of railway line reconstruction projects. The model can be applied for rough and rapid investment value estimations, with a reliability of 80 - 85 % for cases in which some input parameters are unknown. More accurate investment value estimations can be made by including a greater number of input parameters describing the requirements, and by expanding the database of completed rail infrastructure projects.

The application of this model greatly contributes to formulation of a new approach to solving the problem of estimating investment value of railway line reconstruction activities, with the goal of making efficient decisions on investment in rail infrastructure projects.

Acknowledgements

This work is a part of TR 36017 project conducted with the financial support of the Ministry of Education, Science and Technological Development, Republic of Serbia.

REFERENCES

[1] Europski sporazum o najvažnijim međunarodnim željezničkim prugama (AGC), Ženeva, 1985.

[2] AGTC-European Agreement on Important International Combined Transport Lines and Related Installations, Geneva, 1 February 1991.

[3] SEECP (South East European Cooperation Process), Agreement on the establishment of a high performance railway network in South East Europe, Thessaloniki, 2006.

[4] Directive 96/48/EC on the interoperability of the trans-European high – speed rail system, United Nations, 1996.

[5] Privredno stručni skup "Železnička infrastruktura – aktuelno stanje i planirane aktivnosti", Udruženje saobraćaja i telekomunikacija Privredne komore Beograda, Beograd, 2010.

[6] Strategija razvoja železničkog, drumskog, vodnog, vazdušnog i intermodalnog transporta u Republici Srbiji 2008 - 2015, Službeni glasnik RS, 4/2008.

[7] Jovanović, S.: Condition – based decision – making track costs, Railway Gazete International, 2003, pp. 277-282.

[8] Ćirović, G.: Upravljanje investicijama, Visoka građevinsko - geodetska škola, Beograd, 2009.

[9] Vouk,D., Malus, D., Carević, D.: Neuralne mreže i njihova primena u vodnom gospodarstvu, Građevinar, 63 (2011) 6, pp. 547-554

[10] Zurada, J.M.: Introduction to Neural System, West Publishing Company, St. Paul, 1992.

[11] Haykin, S.: Neural Networks, Prentice Hall, New Jersey, 2005.

[12] Adeli, H.: Neural Networks in Civil Engineering: 1989-2000, Computer-Aided Civil and Infrastructure Engineering, 16 (2001), pp.126-142, https:// doi.org/10.1111/0885-9507.00219

[13] Studije opravdanosti projekata revitalizacije i modernizacije, Saobraćajni institut CIP i Institut Saobraćajnog fakulteta Univerziteta u Beogradu, Beograd, 2001.

[14] www. zeleznicesrbije.com

[15] Jovanović, S., Guler, H., Čoko, B.: Track degradation analysis in the scope of railway infrastructure maintenance management systems, GRAĐEVINAR, 67 (2015) 3, pp. 247-258, doi: https:// doi.org/10.14256/JCE.1194.2014

[16] Rebano-Edwards, S.: Modelling perceptions of building quality - A neural network approach, Building and Environment, 42 (2007), pp. 2762–2777, https:// doi.org/10.1016/j.buildenv.2006.07.018

[17] Rumelhart, D.E., Hinton G.E., Williams R. J.: Learning internal representations by error propagation, Parallel distributed processing, Cambridge, MA: MIT Press, 1 (1986), pp. 318-62.

[18] Gunaydın, H.M., Dogan, S.Z.: A neural network approach for early cost estimation of structural systems of buildings, International Journal of Project Management, 22 (2004), pp. 595–602, https:// doi.org/10.1016/j.ijproman.2004.04.002

[19] Kim, G.H., An, S.H., Kang, K.I.: Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning, Building and Environment, 39 (2004), pp.1235–1242, https:// doi.org/10.1016/j.buildenv.2004.02.013

[20] Yu, W., Skibniewski, M.J.: A neuro-fuzzy computational approach to constructability knowledge acquisition for construction technology evaluation, Automation in Construction, 8 (1999), pp. 539–552, https:// doi.org/10.1016/S0926-5805(98)00104-6

[21] Dreyfus, G.: Neural Networks: Methodology and Application, Springer-Verlag, Berlin, pp.193-194, 2005.

[22] Knežević, M., Zejak R.: Neuronske mreže - primjena za izradu prognoznog modela eksperimentalnog istraživanja za vitke armirano-betonske stubove, Građevinski materijali i konstrukcije, 51 (2008) 1, pp. 41-56