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APPLICATION OF ARTIFICAL NEURAL NETWORKS IN PLANNING TRACK SUPERSTRUCTURE REPAIRS

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The diagnostics of track superstructure, which involves geometric measurements, direct observation and railroad surveillance, provides the basis for making decisions regarding the commencement of repair works. Planning repairs and increasing the probability of making the right decision at the right time also requires knowledge of the basic performance specifications of a given railway line, especially the maximum train speed and the permissible traffic volume. The article discusses a way to plan the repairs of track superstructure using artificial neural networks. It features a description of the process of designing, building and training a neural network, based on which a way to predict the degree of urgency of repairs has been discussed. The conclusions point towards the potential advantages of neurocomputers in the process of track superstructure maintenance.

Keywords: track superstructure, repair planning, neural networks

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1. INTRODUCTION

The most common rail repairs include those requiring the tamping of sleepers using automatic sleeper tamping machines. The basis for making decisions on the commencement of repairs is diagnostics involving geometric measurements, performed to determine the condition of isolated rail sections, and direct observation or surveillance of the track superstructure using video cameras installed with railroad survey vehicles. The diagnostics of track superstructure and the strategies of maintenance thereof are both issues raised in a number of studies. Sakuma et al. [1] discussed a railway line diagnostic system that does not require measurements to be performed by special survey vehicles,which are substituted in this system by devices installed in the wagons of passengertrains travelling according to timetables. The measurement results are sent in real time to the control centre and then processed automatically to be sent further to entities dealing with track superstructure repairs. I. Soleimanmeigouni et al. [2] performed a critical analysis of models of track geometry degradation, considering its non-homogeneity, and found that the evaluation of track condition based only on vertical irregularities – without taking horizontal irregularities and track twist into account – is insufficient. A.R.B. Berawi et al. [3] presented a set of methods to evaluate the track geometrical quality on the Lisbon – Porto line, where the Polish synthetic index of quality *J* was applied. T. Liden [4] conducted a critical analysis of models of track repair planning, and described some of their applications in Sweden. L. Rui et al. [5] developed models for predicting the necessity of ongoing track superstructure repairs. T. R. Jr. Susmann et al. [6] proposed a spectral method to test the track superstructure and rail bed condition, and described a device designed for such tests.
Sadeghi and Askarenejad [7] proposed a qualitative evaluation of track superstructure, based only on the standard deviations of vertical irregularities. The above also made an attempt to substitute testing of the superstructure by means of geometric measurements with the application of Artificial Neural Networks [8].

Artificial neural networks were also applied by A. Meddah and M. Witty [9] to predict rail cracking. Three types of damage occurring in 136-type rails were considered – cracks from fishplate bolt holes, vertical longitudinal railhead cracks and railhead chipping. Based on data from the period 1997-2015, a range of training and test sequences was developed (almost 100000 data entries). The input layer included 10 variables, such as weather conditions, line traffic loading, defect size, rail manufacturers, line and track category, etc. The highest accuracy (82%) was achieved with respect to railhead chipping in summer conditions, and the lowest accuracy concerned the same defect but in winter conditions, which was explained by less precise records of the conditions in which those defects occurred.

2. ASSUMPTIONS

Awareness of the track superstructure condition, essential for repair planning, is based on many equivalent and non-equivalent features. A proper track superstructure repair is one performed at the right time, in the right place, in the right scope, and up to the required standards. Determining the right time for repairs is a condition that greatly influences the fulfilment of other conditions. Planning such repairs requires the consideration of survey results in the form of numbers and visual inspections (observations) of the structure to be repaired, with the findings of such inspections usually described in words. The relative ease of making geometric measurements, i.e. measurements of track irregularities, and the difficulties in quantifying the structure condition lead to the situation that some studies describe the structure condition based only on the standard deviation of vertical irregularities S_z, and thus, in accordance with [6], the condition can be evaluated as follows:

$S_z \leq 1.0$ mm perfect,

$1.0 \text{ mm} < S_z \leq 2.0$ mm good,

$2.0 \text{ mm} < S_z \leq 4.0$ mm satisfactory,

$S_z > 4.0$ mm inadequate

R. A. Andrade and P. F. Teixeira [10] also tend to evaluate track superstructure condition using the standard deviation of vertical irregularities only.

Making a decision to repair some section of a track superstructure based on such a simplified judgement may lead to premature or late repairs. Premature repairs increase the already high costs of railroad maintenance and renewal, which in the case of Europe with its approx. 300 000 km of tracks amount to 15–25 billion euro per year, according to [4]. Late repairs may, in turn, deteriorate the conditions of interfacing between railborne vehicles and tracks, and make the condition of the track superstructure unrepairable to some extent [11].

Evaluating the superstructure condition based on standard deviation values only can be considered an absolute evaluation, i.e. independent of the maximum train speed. It also weakens the significance of the linguistic evaluation of the condition of particular tracks, and so, for example, a rail considered good (S_z = 2.0 mm) at a velocity of 250 km/h is not a model example. Meanwhile, when considering a track with a standard deviation of S_z = 4.6 mm, an inadequate track at a maximum velocity of 40 km/h seems to be an excessively harsh judgement. Hence, it is absolutely crucial to take the velocity V and traffic volume q into consideration in superstructure repair planning as well.

Increasing the likelihood of accurate decisions being made regarding repairs also requires the adoption of additional geometric parameters of track condition and consideration of the most important structural feature of the superstructure, i.e. the one that determines the effectiveness of sleeper tamping – the condition of the railway ballast. Including the ballast condition in the full numerical description is a complex task, requiring many specialised measurements, so extending the scope of the usual diagnostic activities. Taking this regularity into account, the criterion adopted for the evaluation of the railway ballast condition is the occurrence of easily noticeable wet-beds. Based on the above, 4 ballast states have been differentiated, considering the number n of all wet-beds along 200 m of track, the number of their clusters m, and the number of the adjacent sleepers in cluster k.

1. Very good condition: no wet-beds ($n = 0$)
2. Good condition: not more than 5 in total and not more than 2 clusters with 2 sleepers each, ($n \leq 5,\ m \leq 2,\ k < 3$)
3. Sufficient condition: not more than 8 in total and not more than 2 clusters with 3 sleepers each, ($n < 8,\ m \leq 2,\ k < 3$)
4. Inadequate condition: numbers exceeding the limit value of 3.

The described parameters make it impossible to determine a function on the basis of which a decision regarding repairs could be made. Yet, the issue can be solved by taking advantage of artificial neural networks.

3. NETWORK STRUCTURE, NETWORK TRAINING, AND THE OUTCOMES OBTAINED

3.1 THE CONCEPT OF THE NETWORK MODEL STRUCTURE

The application of artificial neural networks in diagnostics raises new possibilities of problem solving, particularly when a diagnosed problem cannot be formalized in numerical space or additional factors affecting its final outcome could not be taken into consideration [13].

It is an entirely different approach to diagnostics in reference to highly detailed expert systems based on detailed calculations [13-15] supporting decisions relating to the action plans, mainly concerning repairs.

Forecasting the durability of selected railway superstructure parts, taking into account the highest number of examples, is possible with the application of artificial neural networks. It means that artificial neural networks do not require programming and learn on a certain set of examples describing a phenomenon, called a training sequence. The outcome of the training process is to generate complemented relations in the form of interpolation as well as extrapolation [13]. This process allows taking into account indefinable factors.

‘With the application of artificial neural networks, the nature of the task makes it possible to solve it if defined as a predictive problem considered as either classification or regression. The main difference between regression and classification is that in the case of the latter the predicted variable assumes a categorical value (discrete qualitative variable – classes), and in the case of the former, its aim is to predict the value of a variable assuming a continuous value (numerical – continuous – variable). In the case of classification, decisions are based on assigning a new case to one of the known categorical values of the training set, and in the case of regression, prediction involves calculating a new decision value for a given case [16].
Decisions regarding repairs will be made based on an analysis of regression, which is the most appropriate statistical method for the task in question, as it makes it possible to describe the relationships occurring between the input variables and the output variables.

The process of building a regression model consists of the following stages:

a) compiling a data set and determining the nature of variables,
b) selecting the type and determining the structure of the neural network – followed by its training,
c) evaluating and utilising the model in practice.

The aim of the task is to develop a model that can be used to predict the degree of repair urgency *N*. The regression model was built using the collected data, divided into three sets (SSN sequences): a training set, a test set, and a validation set.

The training set is used directly to modify network weights, i.e. to teach the model. The test set is used to monitor the training process. It determines the quality (accuracy) of the prediction of *N*, and re-evaluates the quality of the model after the training stage. It is not, however, involved in the process of network training. The validation set is a completely independent set, i.e. not involved in the stage of either training or testing. It is used as the basis to determine if the model works correctly.

3.2 DATA SET USED TO BUILD A NETWORK MODEL

The preparation of a training set consists in collecting examples, i.e. specific and verified cases and possibly data coding (the input values are to be presented as numbers). In the analyzed task all the input data have numerical features [12]. The set of data to construct a model consists of randomly selected cases from track geometry measurements data gathered over several years and carried out and made available by PKP PLK SA within commissioned tasks in the area of railway lines diagnostics. They include descriptive data and results of measurements performed with the use of electronic track gauge and a measurement handcar on the railway network in Poland. Particular attention has been drawn to the data related to track sections differing in terms of maintenance status, speed and transport volume.

The cases define selected characteristics of tracks, described by means of six parameters referred to by default as the input layer and of the number *N* assigned to them, being a decision value defined as the output layer (Fig. 1).

A training sequence covering information concerning 100 sample track characteristics drawn from randomly selected railway lines in different condition has been developed (the data concerning a given single railway line is included in one row). Each row features values of the seven variables (Table 1).

Table 1. Fragment of training sequence defining the level of repair urgency- *N*

No.	Input layer						Output layer	Sample
	Sz	*Sy*	*Se*	*w*	*b*	*Id*	*N*	
1	4.43	3.76	3.56	5.34	4	1.8	5	U
2	1.04	1.32	0.89	2.14	1	0.6	1	U
3	1.95	2.14	1.06	2.45	2	1.1	2	U

Two of them: the ballast condition *b* and the degree of repair urgency *N* have been determined by the authors based on the following classification:

b – railway ballast condition: 1 – very good, 2 – good, 3 – satisfactory, 4 – inadequate,

N – degree of repair urgency: 1 – repair unnecessary, 2 – planned in a normal mode, 3 – urgent planning, 4 – emergent repair, 5 – emergent repair and speed restriction.

The transport intensity I_d comprises the maximum speed *V* and transport volume *q* on railway lines of the analyzed tracks. The other four, i.e. standard deviations of vertical *Sz*, horizontal *Sy* unevenness, track gauge *Se* and maximum track twist *w*, are results of measurements of track geometry performed on PKP PLK S.A. lines network by special measurement hand cars (EM-120).

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Based on the adopted principles of building a training sequence (Sample U) consisting of 100 cases, two independent sequences have been developed: a test sequence (Sample T) consisting of 40 cases and a validation sequence (Sample W) including 55 cases. Special emphasis has been placed on making sure that each sequence contains different cases.

3.3 NETWORK BUILDING AND TRAINING

There are many types and kinds of neural networks, different in terms of their structures and principles of functioning. Two kinds of neural networks have been developed to predict the repair urgency degree *N*, each of them utilising a different architecture:

- MLP: a multi-layer perceptron feed-forward network,
- RBF: a radial basis function network.

The diagram of the multi-layer perceptron feed-forward (MLP) network is featured in Figure 1.

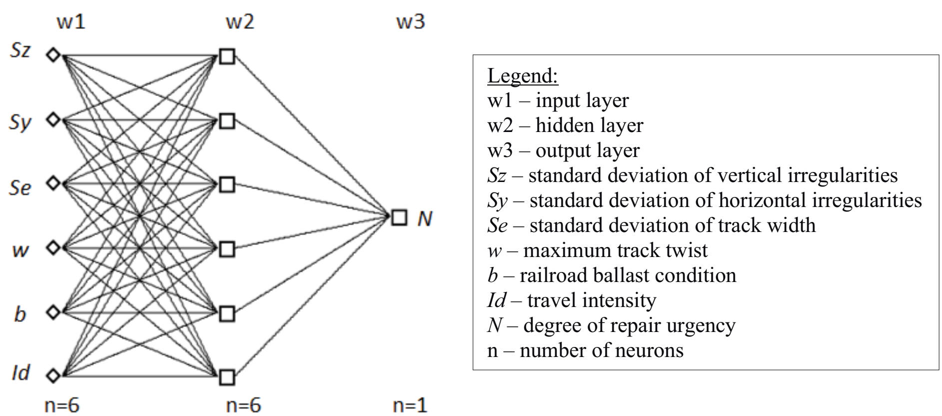


Fig. 1. Designed neural network, MLP 6-6-1

The main features of an MLP-type network are an input layer, a hidden layer (one or several), an output layer, and a set of connections between each of these layers. This means that the network model is formed of neurons arranged in layers with signals transmitted from the input to the output. An MLP-type neuron is determined by its weights and threshold value which, when combined, create an equation of a line and indicate the rate of changes in the value of the transfer function (activation function). Determining the right number of layers and neurons and the activation function that calculates a neuron's output value is a very important element of the process of building such a network [16, 17].

Training multi-layer networks takes place in the 'teacher' mode, which means that the training set will include values entered at the network input and a range of corresponding output values. The training aims to minimise the rate of occurrence of network error, calculated based on the output values and the values arrived at using the network. The error is calculated by means of a square sum function [12, 16, 17].

RBF networks make it possible to model more complex functions. In order to build an effective model, it is necessary to determine a greater number of neurons in the hidden layer. The main unique feature of this network type is that its hidden layer is formed of so-called radial neurons. A radial neuron is defined by its *centre* and the *radius* parameter, and the Gaussian activation function [16, 17].

Training an RBF network involves three stages:

- determining the radial centres (points), determining the weights for each radial neuron through points of the maximum output value of a given neuron,
- determining the radial deviations (radii), adopting the parameter determining the shape of the activation function, mapped as the threshold value of a given radial neuron,
- determining the weight of the output layer neuron.

3.4 NETWORK DESIGN AND TRAINING

The network design involved building models using a module of automatic network architecture search and indicating the parameters enabling determination of the search range. This made it possible to determine the nature and number of the input (n = 6) and output (n = 1) variables, the activation functions for the neurons of the hidden and output layers as: linear, logistic, tanh, and exponential, and to define the minimum and maximum number of neurons in the hidden layer, i.e. from 3 to 11. The number of the built networks (12) and of the best networks saved (40) was determined as well. Training each of the built networks involved taking advantage of the available solutions, which included a random selection of the network typology and the indicated activation functions. This involves choosing the weight values and the threshold values of all neurons in a way that ensures the minimisation of network error occurrence. The process of training involving the automatic modification of weights and thresholds is based on the data entered, i.e. the parameters of the input layer and the correct solutions thereto [13, 16, 17].

From among the 120 generated networks, there were three best networks bearing the following numbers: 105 (MLP 6-6-1), 11 (MLP 6-6-1) and 35 (MLP 6-5-1) (Table 2) left for further analysis.

In the case of the RBF-type network, the minimum and maximum numbers of neurons in the hidden layer were defined; the defined range was 3 to 25. The numbers of built networks (80) and best networks saved (40) were determined.

From among the 80 generated networks, there were three best networks bearing the following numbers: 20 (RBF 6-14-1), 41 (RBF 6-19-1) and 38 (RBF 6-22-1) (Table 2) left for further analysis.

Table 2. Best MLP - and RBF - type neural networks

No.	Network number	Network name	Quality Training Sample	Quality Testing Sample	Activation Function w2	Activation Function w3
1	105	MLP 6-6-1	0.978	0.925	Tanh	Logistic
2	11	MLP 6-6-1	0.979	0.921	Exponential	Logistic
3	35	MLP 6-5-1	0.973	0.920	Exponential	Tanh
4	20	RBF 6-14-1	0.906	0.912	Gaussian	Linear
5	41	RBF 6-19-1	0.909	0.911	Gaussian	Linear
6	38	RBF 6-22-1	0.945	0.909	Gaussian	Linear

3.5 MLP - AND RBF – TYPE NETWORKS – TESTS AND RESULTS

In the task in question, the best results were achieved for the MLP-type network group. The built networks were evaluated based on *Quality*, determined on the basis of the test sample, which was not involved in the network training stage. The results are provided in Table 2. It appeared that the best network in the MLP group network was network no. 105, MLP 6-6-1, composed of 6 neurons in the input layer, of 6 neurons in the hidden layer, and of 1 neuron in the output layer (Fig. 1).
A synthesis of the results obtained for the MLP network (Figures 2 and 3) illustrates the dispersion of the repair urgency degrees (N_w) arrived at in relation to the values entered (N_{Zm}).

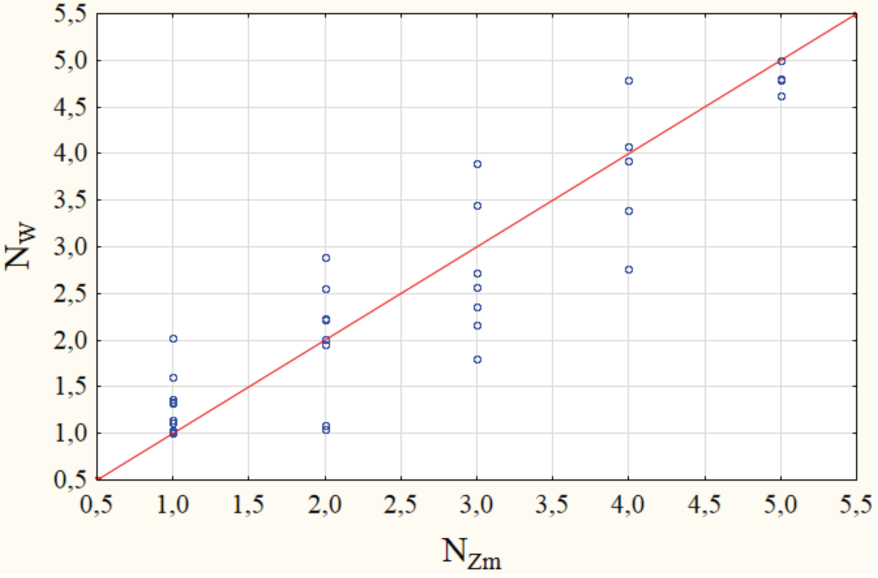


Fig. 2. Dispersion of actual values N_{Zm} (Dependent variable) and predictions of N_W (Output) in network no. 105, MLP 6-6-1 in the test sample

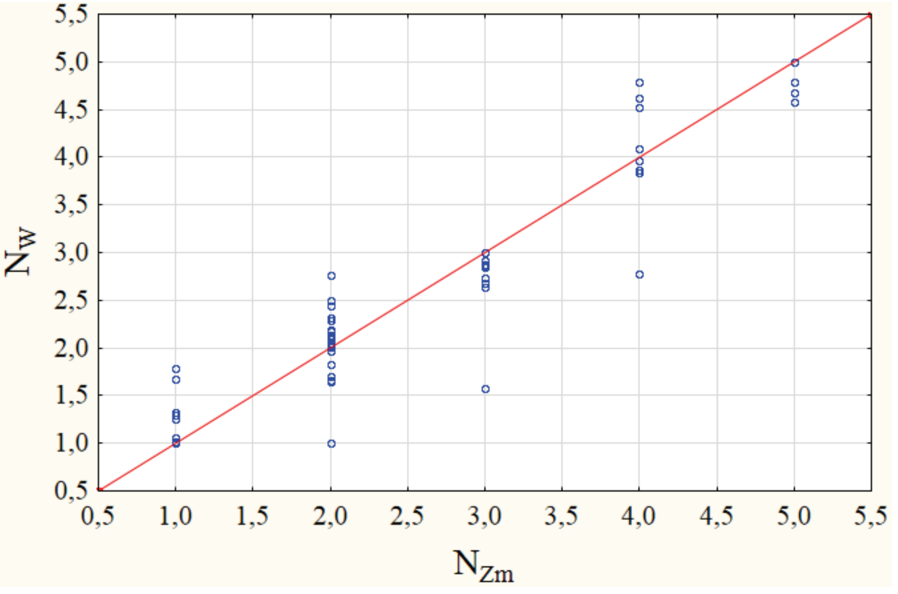


Fig. 3. Dispersion of actual values N_{Zm} (Dependent variable) and predictions of N_W (Output) in network no. 105, MLP 6-6-1 in the training sample

Table 3. Network testing – results

No.	Network number	105	11	35	20	41	38
	Network name	MLP 6-6-1	MLP 6-6-1	MLP 6-5-1	RBF 6-14-1	RBF 6-19-1	RBF 6-22-1
Training Sample							
1	Mean absolute error	0.182	0.179	0.237	0.493	0.495	0.382
2	Mean relative deviation	0.082	0.086	0.130	0.241	0.237	0.216
Testing Sample							
3	Mean absolute error	0.413	0.414	0.437	0.562	0.539	0.480
4	Mean relative deviation	0.193	0.198	0.212	0.273	0.249	0.250

Based on the results of tests of all types of networks, as shown in Table 3, it can be concluded that the best network is the one offering the smallest *absolute error*, determined on the basis of the test set. The *mean absolute error* in the test sample of network no. 105 is 0.413 (19.3%), which is the lowest value among the results for all other networks. The results are proven by a final evaluation of the network's performance, based on the validation set. Based on the network check performed on the Validation Sample it can be argued that the model has been built properly and is stable.

When analysing the results for the predictions of the repair urgency degree N as shown in Figure 3, we can notice that the network is relatively well suited to the task in question. The network performs best in the case of predictions for the numbers $N = 1$ and 5. The prediction N within the range of 2 to 4 has caused some difficulties, which prompts a further discussion on the modification of the training sequence.

3.6 AN ATTEMPT TO IMPROVE THE NETWORK MODEL STRUCTURE

Based on sources [6] and [10] as well as my own professional experience, it appears that the standard deviation of vertical irregularities greater than 2.0 mm may not mark a good track, and a standard deviation of 4.0 mm means that the track is in bad condition. An analogical claim can be made regarding the standard deviation of horizontal irregularities. The values of track twist have a completely different significance, and so $w < 4\ ^{o}/_{oo}$ does not mean that a track is in bad condition (Fig. 5). The condition becomes bad when the track twist value approaches the permissible limit value, i.e. $7\ ^{o}/_{oo}$.

To avoid a disproportionately large impact of track twist values lower than approx. 5 $^{o}/_{oo}$ on the necessity to order repairs, a new experiment was conducted, which involved entering a default quantity t in the input layer to substitute the track twist w according to the following equation:

$$t = 0.1w^2 + 0.02w \tag{3.1}$$

The relationship, lessening the significance of track twist (Fig. 4), was implemented in all SSN sequences, which was followed by the network being built again.

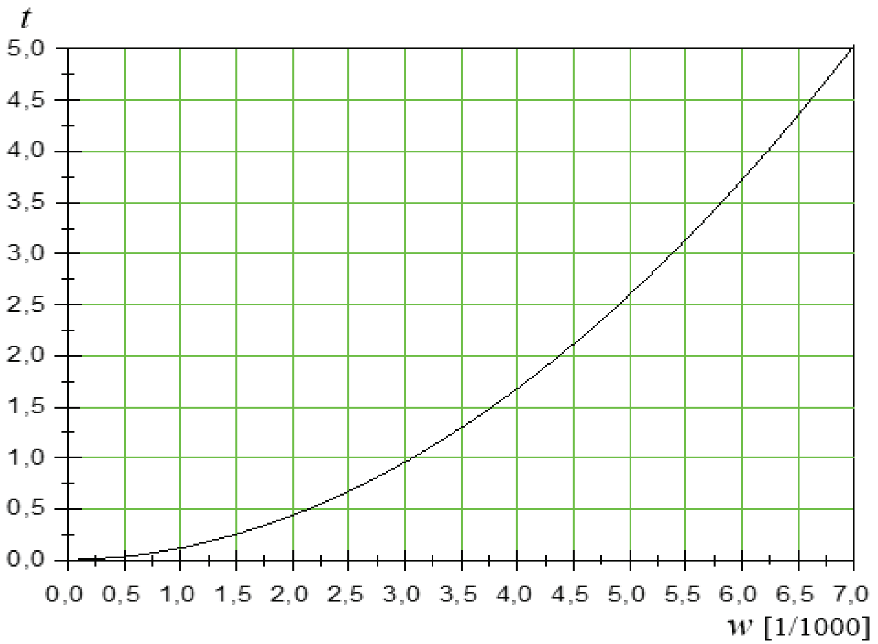
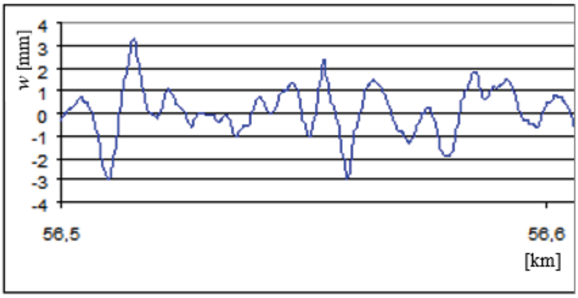


Fig. 4. Relationship between track twist w and its conversion value



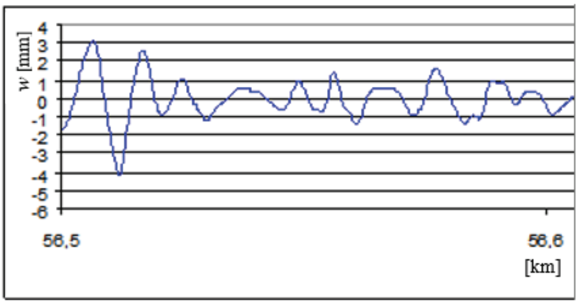


Fig. 5. An excerpt from track twist measurement results [mm/m] provided by a recording coach travelling along approx. 100 m of a railway line track with a maximum velocity of 200 km/h

By analogy, the processes of network building, testing and evaluation were repeated, designing new models as presented in Table 4.

Table 4. Network testing – results for the network after modification of the input layer

No.	Network number	19	24	29	40	36	33
	Network name	MLP 6-5-1	MLP 6-8-1	MLP 6-7-1	MLP 6-5-1	RBF 6-16-1	RBF 6-9-1
			Training Sample				
1	Mean absolute error	0.163	0.156	0.195	0.159	0.295	0.380
2	Mean relative deviation	0.070	0.067	0.101	0.07	0.146	0.179
			Testing Sample				
3	Mean absolute error	0.358	0.392	0.426	0.407	0.490	0.501
4	Mean relative deviation	0.167	0.186	0.194	0.194	0.220	0.226

As a result of the change made in the input layer, the results for both network types were improved. The best network, also in the MLP group, is network no. 19, MLP 6-5-1, composed of 6 neurons in the input layer, of 5 neurons in the hidden layer, and of 1 neuron in the output layer. The *mean absolute error* for the Test Sample for network no. 19 is 0.358 (16.7%), which means a 3% improvement.

4. CONCLUSIONS

The obtained results show that it is possible to plan track superstructure repairs while taking advantage of neural networks. At first, this could be applied to only the most frequent works, i.e. track tamping – preceded in some cases by ballast cleaning. Planning would be based on regular geometric measurements performed using a recording coach and on the outcomes of inspection tours aimed at determining the condition of features and structures, especially of ballast.

Further steps, apart from developing the neural network models, could involve research into the automatic recognition of track superstructure images already recorded by a new recording coach currently in use in Poland. If this proved to be successful, it would legitimise the building of neural networks for hardware implementations, i.e. the employment of a neurocomputer. Such a solution would open the door to the planning of not only retamping but also major repairs – meaning regular renewal of tracks. Feeding neurons with the results of mass defectoscopic tests of rails into a neurocomputer would not only lead to a substantial improvement of the level of rail traffic safety but also make it possible to increase the time of rail service to a great extent.

REFERENCES

1. K. Sakuma, K. Takeda, J. Sato: Monitoring of track maintenance in pursuit of Condition Based Maintenance (CBM). Japanese Railway Engineering 2018, No. 201, 9-12.
2. I. Solemaimanneigouni, A. Ahmandi, U. Kumar: Track geometry degradation and maintenance modeling – A review. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transid, pp. 59-63, July 2016.
3. A. R. B. Berawi. R. Delgado, R. Calcada, C. Vale.: Evaluating track geometrical quality through different methodologies. Journal of Technology, 38-47, 2010.
4. T. Liden: Railway infrastructure maintenance - A survey of planning problems and conducted research. Transportation Research Procedia, Vol.10, 574-583, 2015.
5. L. Rui, M. Wen, K. B. Salling, O. A. Nielsen, A. Landex, S. N. Madsen: A predictive maintenance model for railway track. DTU – The Research Information System, Technical University of Denmark, 2015.
6. J. Sadeghi, H. Askarenijad: Development of improved railway track degradation models. Structure and Infrastructure Engineering (6), 665-678, December 2010.
7. T. R. Jr. Sussmannn, H. B. Thompson, T.D. Stark, S.T. Wilk, C.L. Ho: Use of seismic Surface wave testing to assess track superstructure condition. Construction and Building Materials, Vol. 155, 1250-1255, ELSEVIER, November 2017.
8. J. Sadeghi, H. Askarinejad: Application of neural networks in evaluation of railway track quality condition. Journal of Mechanical Science and Technology, Vol. 26, is. 1, 113 – 122, 2012.
9. A. Meddah, M. Witty: TTCI conducts neural network analysis for rail flow prediction. Railway Track and Structures 2019, No 4, 9-12.

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10. R. A. Andrade, P. F. Teixeira: A. Bayesian model to assess rail track geometry degradation through its life-cycle. Research in Transportation Economics 36(1), 1-8 2012.
11. H. Bałuch: Determinanty wymian nawierzchni kolejowej (Determinants of railway superstructure replacement), Vol. 175, 7-14, 2017.
12. H. Bałuch, M. Bałuch: Sieci neuronowe jako narzędzie rozwiązywania problemów z zakresu dróg kolejowych (Neutral networks as tools to solve problems on Railway Lines). Problemy Kolejnictwa, Vol. 124, 35-62, 1997.
13. M. Bałuch: Interpretacja pomiarów i obserwacji nawierzchni kolejowej (Interpretation of railway superstructure measurements and observations). Technical University of Radom Publishing House 2005.
14. H. Bałuch: System geometryczno-kinematycznej oceny toru kolejowego (Geometric-kinematic system of railway track assessment). Problemy Kolejnictwa, Vol. 136, 2002.
15. H. Bałuch: Systemy eksperckie w diagnostyce nawierzchni kolejowej (Expert systems in railway superstructure diagnostics). Problemy Kolejnictwa, Vol. 114, 1993.
16. StatSoft. Elektroniczny Podręcznik Statystyki PL (Electronic Statistics Textbook PL), Cracow, 2006. WEB: *http://www.statsoft.pl/textbook/stathome.html.*
17. R. Tadeusiewicz, T. Gąciarz, B. Borowik, B Leper: Odkrywanie właściwości sieci neuronowych (Discovering Neural Networks' Properties), Polska Akademia Umiejętności, Cracow 2007.

LIST OF FIGURES AND TABLES

ZASTOSOWANIE SZTUCZNYCH SIECI NEURONOWYCH W PLANOWANIU NAPRAW NAWIERZCHNI KOLEJOWEJ

Słowa kluczowe: *nawierzchnia kolejowa, planowanie napraw, sieci neuronowe*

STRESZCZENIE

Diagnostyka nawierzchni kolejowej obejmująca pomiary geometryczne, obserwacje bezpośrednie lub obrazy wizyjne stanowi podstawę do podejmowania decyzji o przystępowaniu do napraw. Planowanie napraw i zwiększenie prawdopodobieństwa trafności podjętej decyzji o właściwym czasie wykonania wymaga też znajomości podstawowych charakterystyk eksploatacyjnych określonej linii kolejowej, głównie zaś maksymalnej prędkości pociągów oraz natężenia przewozów. W artykule przedstawiono możliwość planowania napraw nawierzchni kolejowej przy zastosowaniu sztucznych sieci neuronowych. Scharakteryzowano proces projektowania, budowy i uczenia sieci neuronowej, na podstawie którego przedstawiono możliwość predykcji stopnia pilności naprawy. W podsumowaniu przedstawiono możliwości wykorzystania neurokomputerów w procesie utrzymania nawierzchni kolejowej.

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