DOI 10.20544/TTS2021.1.1.21.p45
UDC••656.2.054:004.891.3..032.26(497.11)
Original scientific paper

Application Of Artificial Neural Networks For Predictions Of Failure Of Railway Signaling Devices

Marko Bursać[1], Sanja Jevtić[2] and Goran Tričković[3]

Abstract – **The maintenance and reliability of the signaling system are one of the key factors when it comes to the safety of rail transport. The objectives of this paper are to define a prediction model for the failure of railway signaling devices. The obtained results can significantly help in maintaining.**

Keywords – **Maintenance, Railway signalling, Failure, Artificial neural network.**

I. INTRODUCTION

This paper presents a model for predicting failure railway signaling devices. A methodologically developed approach to data collection and the creation of an artificial neural network enables the definition of a model of prediction. The results obtained by the prediction can significantly help maintain the organization of business processes and the purchase of spare parts. In addition to organizational aspects, the contribution of research can improve the safety of rail traffic in terms of the reliable operation of the signaling system.

Maintenace in the railway environment was for years grouped in two major streams – investments and regular maintenance. Regular maintenance was based on the type and quantity of the equipment in use. According to the manufacturer's recommendations, a number of measurements and actions were to be taken during the maintenance year (some monthly, some semi-year, some even daily) [1].

Even though most of the systems are outdated and on the rising part of the failure rate curve $\lambda(t)$ [2, 3] some enhancements could be done in the organization, that could greatly influence the prediction of failures, thus enabling the reduced number of staff to easier coordinate maintenance and not just react in the case of emergency.

The existing failure database dealing with communication equipment is organized in such a way to enable even the end-users to report a failure (large lots without details). The maintenance staff further fill in the reasons and development of failure. With the improvement of description and outcome of failure, it could be possible to better understand, monitor, and even predict certain failures [1].

II. MATERIALS AND METHODOLOGY

Failure database which is the object of consideration in this paper deals with all communication systems. For the purpose of making the procedure and conclusions transparent a large part of it was chosen for study. The time span of this database is January 2013 – June 2018.

The database from which the records were downloaded was formed for the purpose of recording failures on telecommunication and signaling devices used on the railway. All employees have access to the database, while engineers at Belgrade Marshaling Yard are updating the database.

Based on the available literature, artificial neural networks provide adequate data prediction. The data presented in this study were exported from a failure database, classified and organized within an artificial neural network (input, target and output data).

After the classification and prediction of failures of signaling devices on the railway, it is possible to create comparative graphs of actual failures and failures provided by an artificial neural network.

III. NEURAL NETWORK MODEL FOR PREDICTING FAILURE

Artificial neurons or nodes are the primary processing elements of neural networks. In the mathematical model of ANN, synapses show connection weights and are related to input signals. Furthermore, a transfer function defines the nonlinear characteristic of neurons.

The weighted sum of the input signals which represents the neuron impulse is computed and then transformed using the transfer function. Setting the weights in accordance with the chosen learning algorithm, the learning capability of neurons is obtained [4].

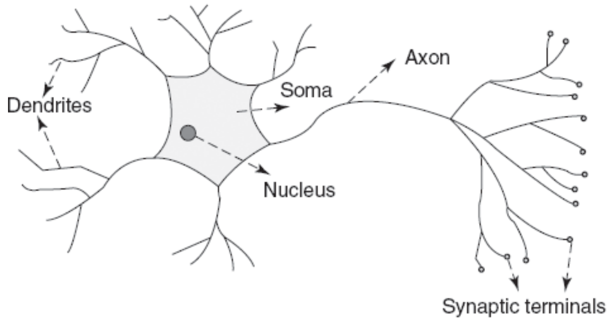

Fig. 1. Neuron

Neurons are often grouped into layers. Layers are groups of neurons that perform similar functions. There are three types of layers. The input layer is the layer of neurons that receive input from the user program. The layer of neurons that send data to the user program is the output layer. Between the input layer and output layer are hidden layers.

[1]Bursać, High railway school of vocational studies, Zdravka Čelara 14, Belgrad, Serbia, marko.bursac@vzs.edu.rs
[2]Jevtić, High railway school of vocational studies, Zdravka Čelara 14, Belgrad, Serbia, jevtic.sanja@gmail.com
[3]Tričković, High railway school of vocational studies, Zdravka Čelara 14, Belgrad, Serbia, tricko86@gmail.com

Hidden layer neurons are only connected only to other neurons and never directly interact with the user program. The input and output layers are not just there as interface points. Every neuron in a neural network has the opportunity to affect processing. Processing can occur at any layer in the neural network. Not every neural network has this many layers. The hidden layer is optional. The input and output layers are required, but it is possible to have one layer act as both an input and output layer [5].

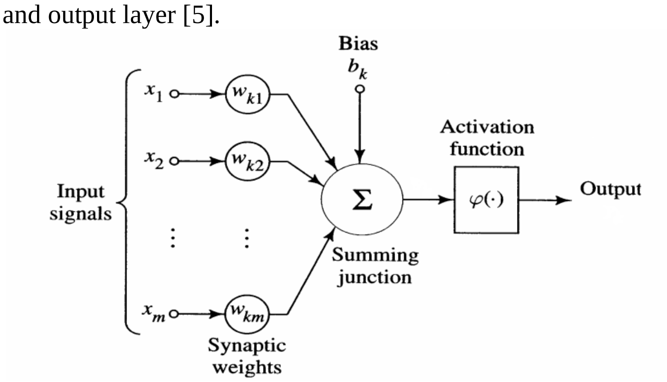

Fig. 2. Artificial neuron [5]

The output for the single neuron illustrated above is described in by,

$$O_n = \varphi(b_k + \sum_{i=1}^{m} w_{ki} * x_i) \quad (1)$$

where O_n is the output, φ is the activation function, b_k is the threshold bias, w_k are the synaptic weights, x_i is the inputs from the previous layer of neurons, and i is the number of inputs. Every neuron has many connections going to and from other neurons. The information passed on to each neuron may have a very small or large effect on the final output. A threshold limit is used via a bias value in artificial neural networks to simulate the formation and degradation of inter-neuron connections as in the biological system. Large arrays of these neurons supply the ability to map out regions of parameter space defined by the input parameters. Each neuron is capable of editing weights supplied to it based upon the accuracy of the entire network. This enables the neural network to learn the behavior of data provided [6].

The neural network is defined through two phases, the learning or training phase and the testing phase. Prior to learning, it is necessary to define the input and output variables and to collect data to which the backpropagation algorithm will be applied [7].

The backpropagation algorithm uses supervised learning, which means that we provide the network with examples of inputs and outputs [8, 9].

Namely, artificial neural networks can be trained - after a number of iterations, the network loses its generalization property (good classification for unknown inputs) and becomes an expert in processing data from a set of learning examples while processing the remaining data poorly. By constantly monitoring the output from the network obtained by the example from the test set, it is possible to detect an iteration in which the output obtained deviates least from the desired response (Fig. 3). The accuracy and precision of data processing can ultimately be verified over a third set of examples - the validation set [10].

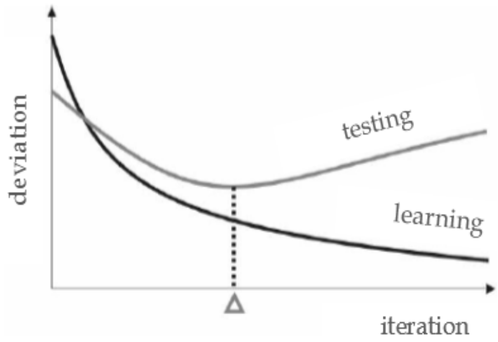

Fig. 3. Deviation of actual output through iterations [10]

The input variables identified are those which can simply be obtained from database. The input and output variables are present in table.

TABLE I
VARIABLES

Variables	Description	Values
Input	Railway station	1 - Adrovac 2 - Aleksinac 3 - Bagrdan 4 - Barajevo . . 106 - Zuce
	System (larger groups to be end user oriented)	1 - station dispatching devices . . 25 - power supply
	Date of failure	01-31 - day
		01-12 - month
		13-18 - year
Output	System	1 - station dispatching devices . . 25 - power supply

In this research, we utilize a multi-layer neural network with one hidden layer of neurons and with feed-forward backpropagation. Model is developed using MATLAB Neural Network Toolbox. The type of algorithm that was selected when creating this network is Levenberg-Markuardt.

The accuracy measure is often defined by forecasting errors that represent the difference between the actual (desired) and the predicted value. There are more such predictive precision measures that are encountered in the literature, each having its own advantages and limitations. The most commonly used Medium Square Error (MSE) according to the equation [11]:

$$MSE = \sum_{i=1}^{N} \frac{(P_{actual} - P_{predicted})^2}{N} \quad (2)$$

where N represents the number of samples, P_{actual} real results and $P_{predicted}$ results obtained by predetermining the neural network.

According to [5], there are many ways to determine the exact number of neurons used in hidden layers:

- the number of hidden neurons should be between the size of the input layer and the size of the output layer.
- the number of hidden neurons should be 2/3 of the size of the input layer, plus the size of the output layer.
- the number of hidden neurons should be smaller than the double size of the input layer.

During the design and testing of the model, the best results are obtained by working with four neurons in the hidden layer of the network, which is in accordance with the above recommendations.

The first three graphs in the picture represent training, validation and testing data. The dotted line on the charts represents perfect results, the result - output = goals.

The full line represents the best linear regression between input and target data. The value of R represents the induction of the relationship between input and target data. If R values 1, it follows that there is an accurate linear relationship between the line relationship between input and target data [12].

During network training, weights between input and output data are changed. In each iteration calculate the new weight to the network gave the smallest error. The learned network in the next step is validated in order to find a better result with memory data. The procedure is repeated until the result improves. The acquired network is tested on a test sample, and the resulting result is taken as the final measure of network performance [13].

IV. Results and Discussion

During the database study, the majority of failures were reported for communication boards, station dispatching devices and cables.

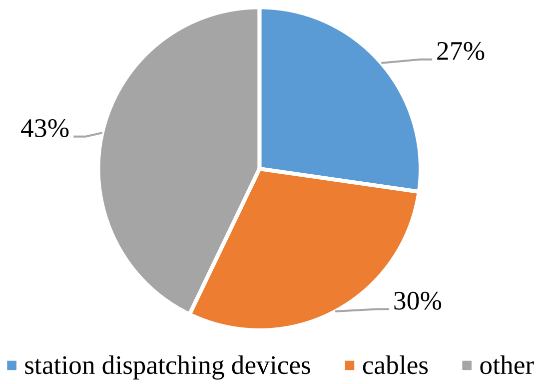

Fig. 4. Types of failures

For example, most of the failures on station dispatching devices and cables were noted in Belgrade Marshaling Yard. In most of the cases, the failure was not tracked to its origin but overridden by reset of the system.

The reason for such cancellation of railway signals is given frequent theft of cables that are unprotected, while for station dispatching devices deterioration states.

Based on the created model, part of the system the prediction of the system that has been canceled is given. The prediction results are shown in the following chart (red color) - Fig. 5.

As a result of training, acceptable correlation coefficient R values were obtained, for training R = 0.74619; for validation R = 0.78097; and for testing R = 0.7243.

The value of R represents the induction of the relationship between input and target data. If R values 1, it follows that there is an accurate linear relationship between the line relationship between input and target data [12].

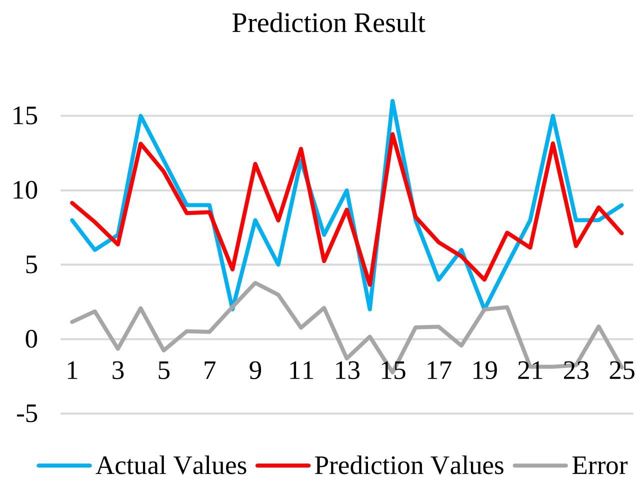

Fig. 5. Prediction result

During network training, weights between input and output data are changed. In each iteration calculate the new weight to the network gave the smallest error. The learned network in the next step is validated in order to find a better result with memory data.

The procedure is repeated until the result improves. The acquired network is tested on a test sample, and the resulting result is taken as the final measure of network performance.

According to the obtained data it is possible to determine the mean square error (MSE) in the following way: for failure 1 - P_{actual} = 8, $P_{predicted}$ = 9.16; for failure 2 - P_{actual} = 6, $P_{predicted}$ = 7.86 and so on. For the total number of observing failures (582 of them).

The results of R values improve with each new test compared to the previous training of the network, and therefore, at each initialization of training of the network, the parameters of the R values change and produce different solutions, ie a new prediction of the output data.

After obtaining the difference between P_{actual} and $P_{predicted}$, it is necessary to sum up all values and divide it by the number of failures. During testing on 582 samples, with one hidden layer (four neurons), the mean square error (MSE) is 9.16.

V. Conclusion

This paper introduced a model, an artificial neural network approach for identification failure Railway Signaling Devices, a neural network developed in the MATLAB program.

The obtained results indicate that the use of neural network models can predict the number of failures on defined systems of the railway signaling infrastructure.

Research has shown that a large number of failures are due to cable breakdowns (frequent thefts), as well as the most frequent breakdowns in Belgrade Marshaling Yard. As one of the results of the research, it can be concluded that a greater measure of implementation of the railway infrastructure protection system is needed.

The prediction results are intended to show the success of failure prediction on signaling devices used on the railway. The results obtained may indicate the need for better organization of maintenance services for signaling devices on the railway, as well as for the possibility of better planning of procurement of maintenance equipment.

Future work could be reflected, first and foremost, in the development of a database with predefined input, which would aim to generate a large number of inputs to the neural network. In addition to re-engineering a database, it would be important to achieve a certain level of automation neural networks. One solution is to create an internet-based application that will make it easier for end-users to work with.

Lastly, in order to implement a failure prediction system on signaling devices used on the rail, it would be necessary to redefine the artificial neural network in order to achieve better prediction results and reduce error.

References

[1] M. Bursać, S. Jevtić, I. Knežević, „Enhancement Of Legacy Communication Systems Maintenance In Railway Environment Using Artificial Neural Network“, 4th International conference on Knowledge management and informatics, Kopaonik, Serbia, 2018.

[2] R. Ramović, *Pouzdanost sistema elektronskih, telekomunikacionih i informacionih*. Elektrotehnički fakultet u Beogradu, 2005.

[3] N. Vujanović, Teorija pouzdanosti tehničkih sistema, VINCA, Beograd, 1990.

[4] A. Ajith, *Artificial neural networks - Handbook of Measuring System Design*, London: John Wiley and Sons Ltd, 2005.

[5] M. Hagan, H. Demuth, B. Hudson, *Neural Network Design - 2nd Edition*, 2014.

[6] C. Lu, *Artificial neural network for behavior learning from meso-scale simulation, application to multi-scale multimaterial flow*, Iowa: University of Iowa, 2010.

[7] R. Craig, N. Attoh-Okine, “A Comparative Analysis of Two Artificial Neural Networks Using Pavement Performance Prediction”, Computer-Aided Civil and Infrastructure Engineering, vol. 13, no. 5, pp. 339-348, 1998.

[8] C. Gershenson, *Artificial Neural Networks for Beginners,* Neural and Evolutionary Computing, 2003.

[9] W. Arif, M. Saduf, “Comparative Study of Back Propagation Learning Algorithms for Neural Networks”, International Journal of Advanced Research in Computer Science and Software Engineering, vol. 3, no. 12, pp. 1151-1156, 2013.

[10] B. Dalbelo Bašić, M. Čupić, J. Šnajder, *Umjetne neuronske mreže*, Zavod za elektorniku, mikroelektroniku i inteligentne sustave, Fakulteta elektrotehnike i računarstva, Zagreb, 2008.

[11] M. Sayyed, “Prediction of Success or Fail of Students on Different Educational Majors at the End of the High School with Artificial Neural Networks Methods”, Journal of Innovation, Management and Technology, vol. 4, no. 5, pp. 461-465, 2013.

[12] Analyze Shallow Neural Network Performance After Training, https://www.mathworks.com/help/nnet/ug/analyze-neural-network-performance-after-training.html [Accessed 07 02 2020].

[13] J. Popčević, I. Varga, P. Žuvela, *Izračunavanje temperature vrelišta uz pomoć umjetnih neuronskih mreža*, Zagreb: Fakultet kemijskog inženjerstva i tehnologije Sveučilišta u Zagrebu, 2012.

[14] Analyze Shallow Neural Network Performance After Training, https://www.mathworks.com/help/nnet/ug/analyze-neural-network-performance-after-training.html [Accessed 11 02 2020].