TECHNICAL TRANSACTIONS | **CZASOPISMO TECHNICZNE**
ELECTRICAL ENGINEERING | ELEKTROTECHNIKA

3-E/2016

DOI: 10.4467/2353737XCT.16.264.6063

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APPROXIMATION OF OVERLOADS FOR A SELECTED TRAM TRACTION SUBSTATION USING ARTIFICIAL NEURAL NETWORKS

APROKSYMACJA PRZECIĄŻEŃ WYBRANEJ TRAMWAJOWEJ PODSTACJI TRAKCYJNEJ Z WYKORZYSTANIEM SZTUCZNYCH SIECI NEURONOWYCH

A b s t r a c t

The article presents some of the results of measurements of loads for a selected tram traction substation for a continuous period of time covering sixteen weeks (112 days). Particular attention was paid to overloads occurring in consequent days. The second part of the article presents the analysis of overloads relating to the time interval of 60 minutes in successive days. This analysis was implemented in Matlab using a two-layer feedforward artificial neural network (ANN). The results of the approximation of the analyzed overloads are promising. A continuation of research may lead to the formulation of mathematical equations that might be useful for designers in terms of sufficiently precise calculations of overloads of rectifier units of DC traction substations.

Keywords: loads and overloads of tram traction substation, artificial neural network

S t r e s z c z e n i e

W artykule przedstawiono niektóre wyniki pomiarów obciążenia wybranej tramwajowej podstacji trakcyjnej dla spójnego okresu czasowego obejmującego szesnaście tygodni (112 dni). Szczególną uwagę zwrócono na występujące przeciążenia w kolejnych dniach realizacji pomiarów. W drugiej części artykułu dokonano przetwarzania przeciążeń odnoszących się do przedziału czasowego 60 minut w kolejnych dobach, z wykorzystaniem sztucznej sieci neuronowej (SSN) dwuwarstwowej typu feedforward, zaimplementowanej w środowisku Matlab. Uzyskane wyniki aproksymacji analizowanego przeciążenia wyglądają obiecująco. Oznacza to, że kontynuując badania, będzie można uzyskać zapis matematyczny, użyteczny dla projektantów w zakresie wystarczająco dokładnych obliczeń (oszacowań) przeciążeń zespołów prostownikowych podstacji trakcyjnych prądu stałego (DC).

Słowa kluczowe: obciążenia i przeciążenia tramwajowej podstacji trakcyjnej, sztuczne sieci neuronowe

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1. Introduction

Variability of loads of rectifier units and other elements of the main circuits of traction substations is no surprise to specialists. The reasons behind this phenomenon are known [3, 8, [12]. Researches and analyses of such loads, which have been conducted for many years both for train and tram traction substations [4, 5, 9, 10], show that the powers of used rectifier units are designed with considerable excess. Reserves in power supply systems are indispensable, exactly because of the variability of traction loads, but as well due to the adjustable structure of these systems, which enables active customization, e.g. adaptation of the number of rectifier units to currently acting loads [2, 7].

Problems relating to the variable nature of the traction loads are confirmed by publications and specialists from other research centers [15–24].

Excessive reserves in power supply systems, compared to actual or diagnosed currents (powers), generate unnecessary investment and operating costs. A reduction of these costs will undoubtedly strengthen the competitiveness of electric rail transport and will also downscale the negative ecological impacts due to lower energy consumption [6].

The article presents research results on the approximation of 60-min overloads for traction loads determined on the basis of measurements for a working tram traction substation [14].

The aim of the research is the improvement of computational methods in terms of the determination of traction overloads, in particular the overloads, which are taken into consideration when designing the number and power of rectifier units for traction substations.

2. Load characteristics of the analyzed traction substation

Registered loads, which were analyzed and are partially presented below, relate to a tram traction substation located in the central part of a big city, on a complex rail and road junction with considerable traffic [4–6].

2.1. Examples of instantaneous traction loads

In order to give the idea of what measured magnitudes are taken into account, Fig. 1 shows examples of the waveforms of instantaneous values of traction currents, which constitute loading of rectifier units of the above mentioned tram traction substation. Waveforms for a weekday (23.10.2013 – Wednesday) and a holiday (27.10.2013 – Sunday) are presented. These test results apply to 2 days, which is approx. 0.55% of the calendar year. The currently used design methods base on the assessment of the annual energy consumption. Following subsections of the article include much longer periods.

Based on these results, it could be concluded that, on the analyzed days, the traction substation „Czyżyny" was not fully loaded [6]. For example, on a weekday, the occurring load was corresponding to the continuous power of four rectifier units, which build the substation, only for approx. 6 minutes (in total). Also, for almost 5 hours in total, the substation (rectifiers) were not under load at all. During this time, all four transformers of the rectifier units took energy from the power supply system just to cover no-load state losses.

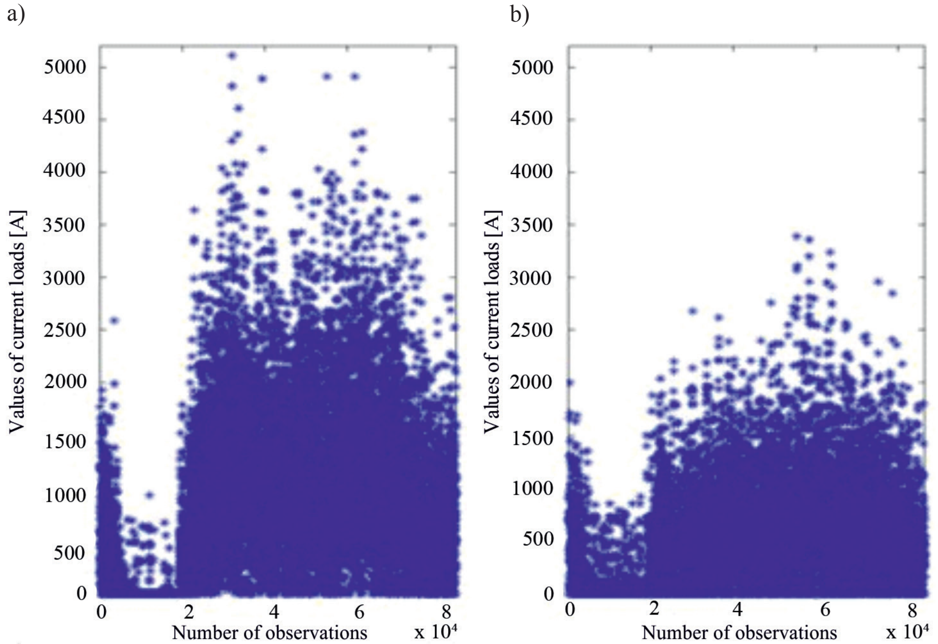

Fig. 1. Registered instantaneous values of current loads of the traction substation „Czyżyny" on: a) 23.10.2013 (Wednesday), b) 27.10.2013 (Sunday). From: [6, 14]

2.2. Traction loads and overloads for a longer time period

This subsection presents measurement results and selected aspects of their analysis [4, 14] for a time period of 16 consecutive weeks in autumn and winter (from 09.01.2014 to 12.21.2014). Some of the presented results were then analyzed using an artificial neural network (Section 3).

Fig. 2 shows the average values of current traction loads in individual weeks of the studied period.

From the above figure, it can be inferred that the substation was bearing different loads with respect to individual weeks. The highest average value of current (the greatest energy consumption) occurred in the 14^{th} week and was equal to 778.74 A, which is 1.25 times more than the average for the period, which in turn is equal to 621.61 A.

Fig. 3a depicts average values of current traction loads in individual days (for a full span of 24 h). On the other hand, Fig. 3b gives the ordered graph of these loads: from the highest value (965.38 A) to the smallest one (304,11 A).

The overload (the overload factor α) is defined as the ratio of the highest load (the highest average current value) lasting for a certain period of time, e.g. 5 min or 60 min, in a given 24-hour period, to the average current value for the same 24 hrs.

Fig. 4a shows 5-minute overload values in individual 24-hour periods. These factors are presented in an ordered manner, that is, from the highest (α_5 = 3.11) to the smallest (α_5 = 2.08). Fig. 4b depicts the diagram of ordered 60-min overloads. One can observe that here the highest value is α_{60} = 2.08 and the lowest value is α_{60} = 1.35.

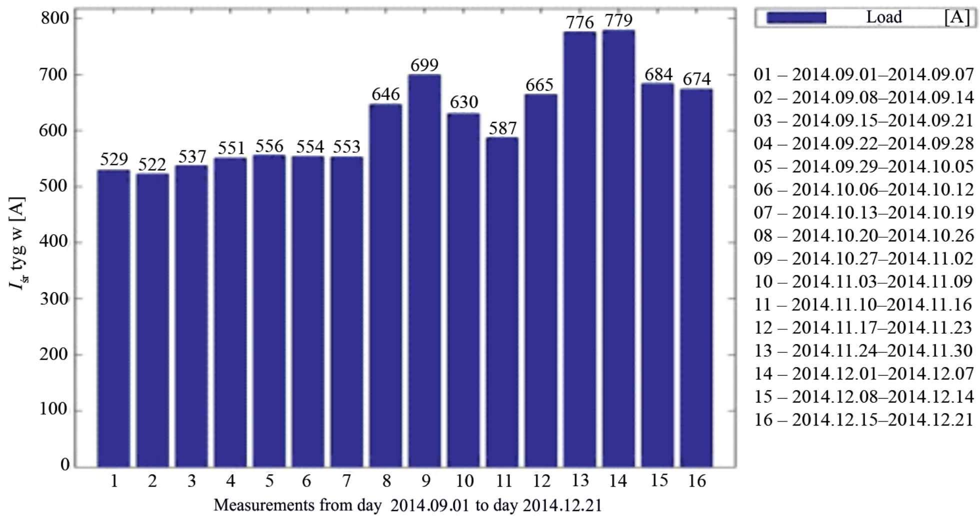

Fig. 2. Average values of current traction loads in individual weeks. From: [4]

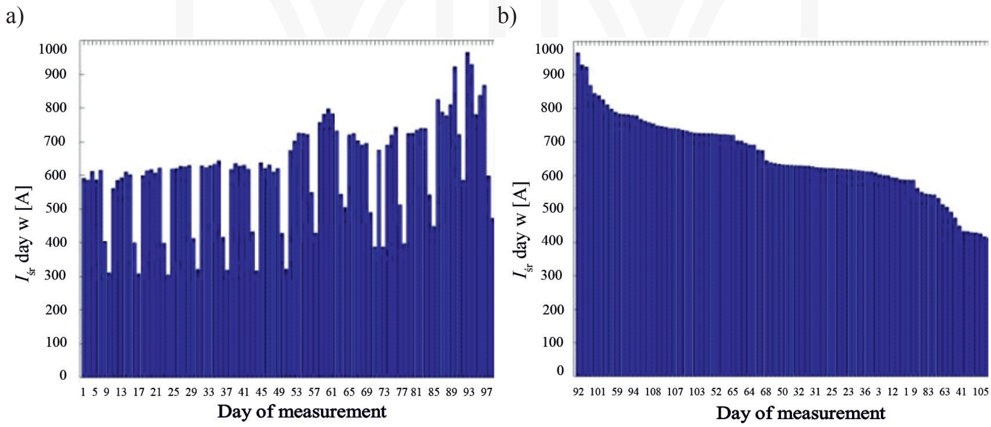

Fig. 3. Average values of current loads of the traction in individual days: a) chronologically, b) ordered. From: [4]

Fig. 5 presents two polylines created by joining the points corresponding to 5-min and 60-min overloads with straight line sections. The points were linked chronologically: from day 1 (01.09.2014), to the last, 112th, day (21.12.2014).

In the above figure, one can see that the overloads in succeeding days assume different values and that 5-min overloads are higher compared to 60-min ones. This observation is not surprising, particularly among specialists. The data in Fig. 5 also easily leads to getting a grasp on the extent to which these values differ.

Fig. 6 depicts the whole range of possible overload changes (overload factors changes), depending on different time periods of the highest load taken for the calculation of the factors. The chosen time periods start from 10 seconds up to 3 hours. The calculations were performed for the measurement data for the above-mentioned 112 days. The abscissa axis refers to time periods of overloads taken for calculations (acc. to Tab. 1); the vertical axis refers to overloads (overload factors). The upper curve is plotted for maximum values, while the bottom one – for minimum values. The area between these curves is the range in which other values of overload factors can occur.

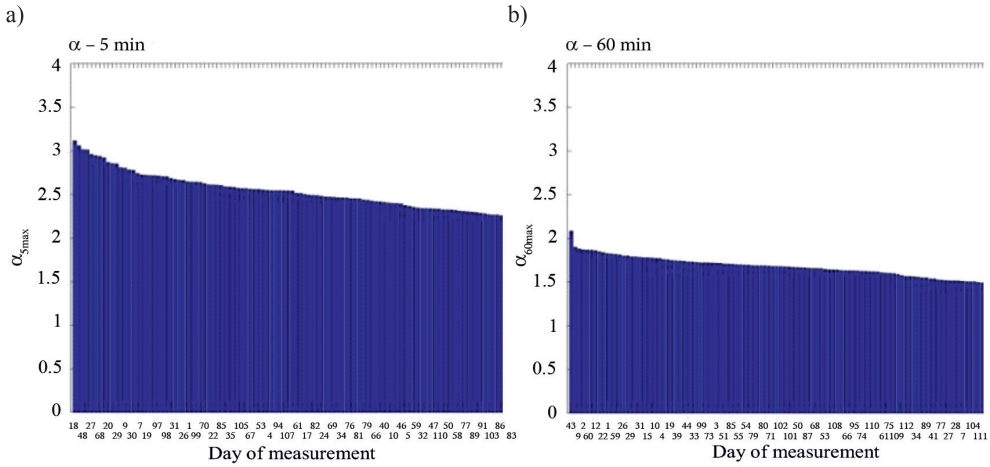

Fig. 4. Maximum overloads ordered from the highest to the smallest value (for 112 days); for time periods: a) 5 min, b) 60 min. From: [4]

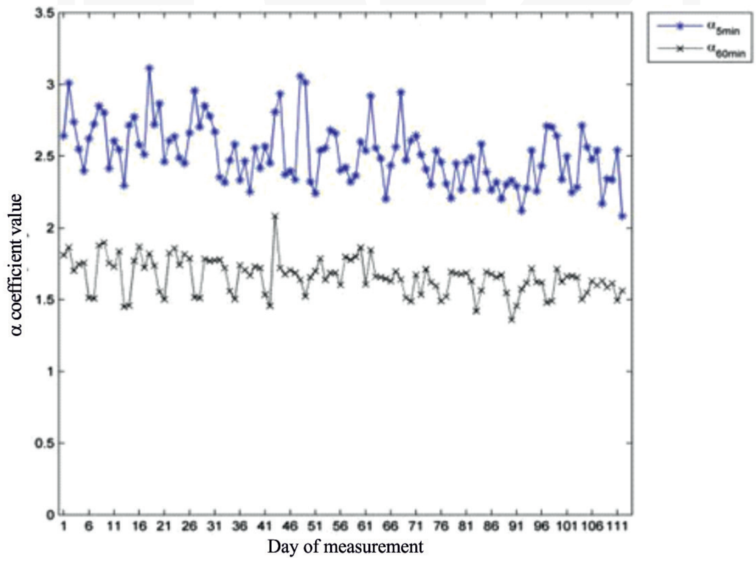

Fig. 5. Changes of 5-min and 60-min overload factors, presented chronologically. Own work

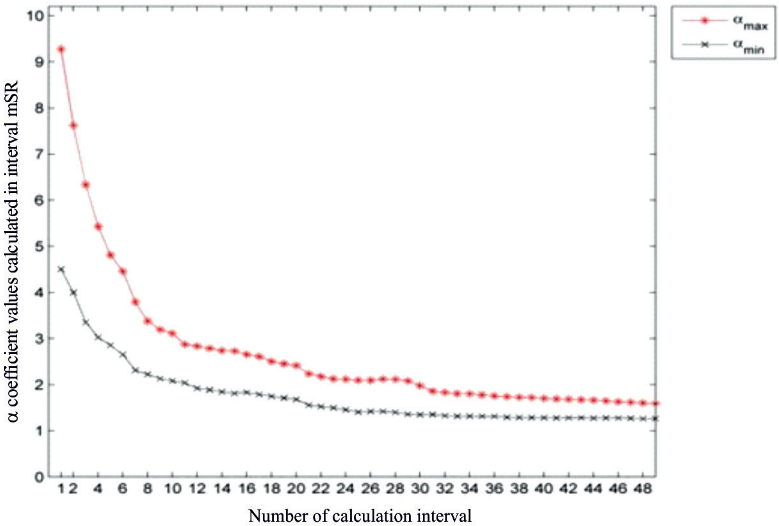

Fig. 6. Values (maximum and minimum) of overload factors for selected time periods. Own work

Table 1

Lengths of time periods taken for calculations to determine changes of overloads (overload factors). Own work

Time period	Lengt [h]	Time period	Lengt [h]	Time period	Lengt [h]	Time period	Lengt [h]	Time period	Lengt [h]	Time period	Lengt [h]	Time period	Lengt [h]
1	2	3	4	5	6	7	8	9	10	11	12	13	14
1.	10 sec	8.	3 min	15.	10 min	22.	25 min	29.	60 min	36.	165 min	43.	270 min
2.	20 sec	9.	4 min	16.	11 min	23.	30 min	30.	75 min	37.	180 min	44.	285 min
3.	30 sec	10.	5 min	17.	12 min	24.	35 min	31.	90 min	38.	195 min	45.	300 min
4.	40 sec	11.	6 min	18.	13 min	25.	40 min	32.	105 min	39.	210 min	46.	315 min
5.	50 sec	12.	7 min	19.	14 min	26.	45 min	33.	120 min	40.	225 min	47.	330 min
6.	60 sec	13.	8 min	20.	15 min	27.	50 min	34.	135 min	41.	240 min	48.	345 min
7.	2 min	14.	9 min	21.	20 min	28.	55 min	35.	150 min	42.	255 min	49.	360 min

3. The use of an artificial neural network in the analysis of a selected overload

Artificial neural network (ANN) is a general name for mathematical structures and their software or hardware models, which perform calculations or signal processing by rows of elements called artificial neurons. Artificial neurons realize some basic operations on their input. The original inspiration for ANNs was the structure of natural neurons, synapses connecting the neurons and nervous systems, especially a brain [11, 13].

3.1. Introductory information and input data

The calculations were performed using Mathlab R2011B version. The input data for the ANN analysis were in this case 112 pairs of numbers. In each pair one of the numbers (Input) was the average value of current on a given day (Fig. 3) and the other number (Output) was the corresponding 60-min overload (the overload factor) for the same day (Fig. 4b).

Measurement data processing was performed using a two-layer feedforward neural network implemented in Matlab. Fig. 7 shows the neural network block created in the Simulink environment.

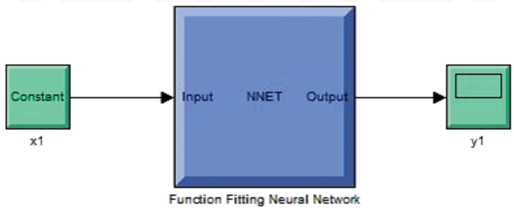

Fig. 7. The neural network block created in the Simulink environment. Own work

Fig. 8 depicts the created neural network structure. This structure had one hidden layer consisting of four neurons. There were no delays implemented on the input for this layer. The activation function for the hidden layer was tangensoidal (tansig). The output layer had a linear activation function.

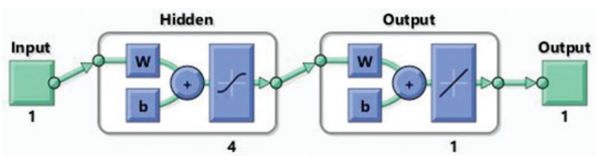

Fig. 8. The created neural network structure. Own work

The aim of the study was to approximate the function that would relate the average load value for a traction substation in a given day with the overload factor – in this case for the time period of 60 minutes.

The results shown below in Subsection 3.2. were obtained for the following ANN training settings [1]:

- maximum number of epochs to train: 1000;
- performance goal: 0;
- learning rate: 0,01;
- maximum validation failures: 12;
- momentum: 0,9;
- minimum performance gradient: 10^{-10};
- epochs between displays: 25;
- maximum time to train in seconds: infinite.

In order to teach the designed artificial neural network, the one-way network (up to 3 layers) training was used according to the Leveneberg-Marquardt algorithm.

3.2. Computation

Fig. 9 depicts results obtained from the training, validation and test of the ANN in the form of an error histogram.

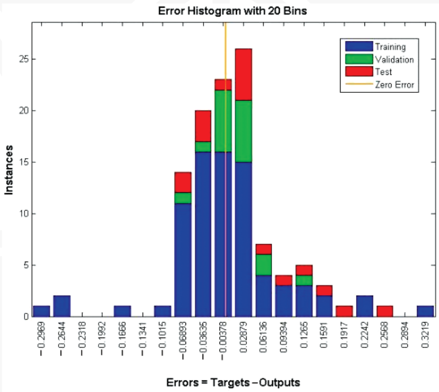

Fig. 9. Error histogram. Own work

Fig. 10 shows the illustration of performance of the ANN for successive learning epochs.

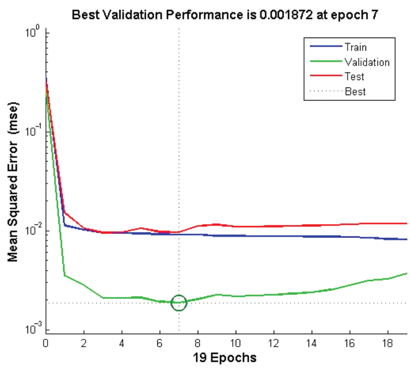

Fig. 10. Performance of the ANN. Own work

Fig. 10 presents the artificial neural network performance graph during its learning. The ordinate axis refers to the ANN performance function values. Mean square error (mse) was chosen as the performance function. The horizontal axis corresponds to learning epochs. The system reached the best neural network validation of the ANN performance for the 7th epoch and it was equal to 0.001872. One can observe that the neural network system continued the learning algorithm for another 12 epochs in order to confirm the alleged local minimum for the goal set for the created network structure (Fig. 8). From epoch 1 to 7, a downward trend in validation tests of the ANN learning can be seen.

Fig. 11 depicts the regression results for the training, validation and test and the regression for all data assigned to the ANN learning with a supervisor. Here, the ordinate axis represents the neural network output for the given input data. The abscissa axis shows values from the actual measurements (targets), to which the values returned by the ANN should be convergent.

The $R = 1$ regression result means that there is an unequivocal relation between the actual value (target; from measurement or simulation) and the neural network output value.

The regression results for the discussed case are as follows. The regression for the data assigned to the training reached $R = 0.65986$. The data constituted about 70% of all data assigned to the ANN learning with a supervisor. The regression for the validation was equal to $R = 0.9113$. The data used for this step were about 15% of all data. Lastly, the regression for the test was $R = 0.69163$. Consequently, the data used in this stage was about 15% of all data. One more regression value was calculated, for all data, and it was equal to $R = 0.68304$.

The training, validation and test are performed during the procedure of the neural network learning.

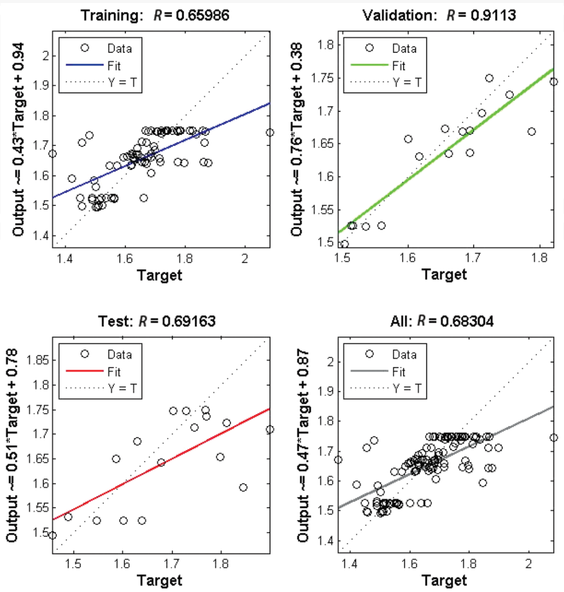

Fig. 11. Regression results for the training, validation and test and the regression for all data assigned to the ANN learning with a teacher. Own work

Fig. 12 presents the results obtained from the approximation process (function fitting process) performed by the artificial neural network learning. In this figure dots represent actual values of the factor α obtained from measurements (targets), while cross marks represent results of the approximation. Vertical lines are absolute errors between actual values and the corresponding results obtained by the function fitting process. The solid line is the plot of the resulting approximating function.

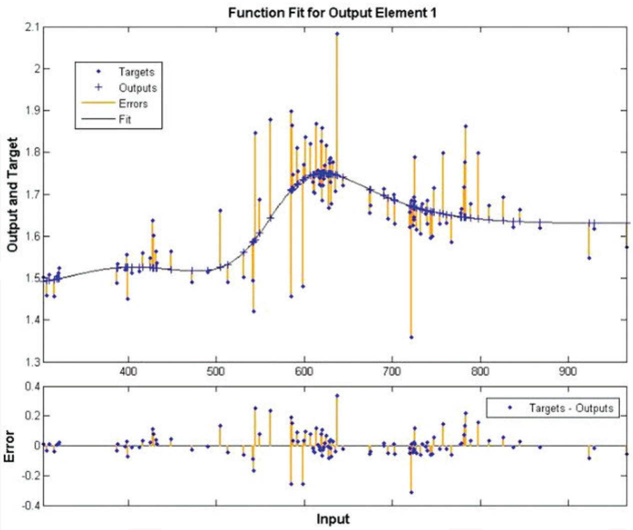

Fig. 12. Results of function fitting with the use of the ANN. Output – the overload factor, input – the average value of current on a given day. Own work

4. Conclusions

The calculation results are promising. Getting to know the possibilities (specificity) of neural networks applied for studies of variability parameters of traction loads should contribute to the formation of conceptual solutions for qualitative changes in the design and construction of power supply systems for railway and tram lines. In effect, this should lead to the reduction of energy consumption and, in particular, to the reduction of various kinds of losses in the power system. Other positive results should be: the improvement of economic competitiveness of electric rail transport and the reduction of the emission of harmful agents into the atmosphere. In further studies, the authors are going to analyze the relation of hidden neurons' impact on the result.

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