

Design and research on artificial neural networks as electrical power system development models based on IEEE RTS data

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The paper presents selected results of research on the design of artificial neural networks and training them using the electrical power system development model (EPS or EP system) based on IEEE RTS 96 test data, i.a. creation of training and test files, development of architecture of the artificial neural network, selection of parameters of the network, selection of appropriate training and testing method, etc. As a result of the development and training an ANN, the following EP system development models were obtained, which were examined for sensitivity to changes of the number of hidden layers, number of neurons in a layer, activation function, training method, etc. Subsequently, simulation models for studying fitness of the obtained models to the real systems. Interesting results were obtained, e.g. the method of the neural modelling of the system, the optimal architecture of the ANN that is a model of the system, possibilities and directions to improve a neural model of the system, etc.

KEYWORDS: artificial neural network, IEEE RTS data, electrical power system, MATLAB and Simulink environment, testing sensitivity, simulation studies

1. Introduction

1.1. Neuronal modelling of the EP system development

Due to the increased need to study the development of the large systems such as electrical power system (EPS or EP system), new methods of modelling are being searched for [5, 24, 26]. Apart from traditional methods such as analytical and identification methods, new methods have increasingly been classified as modelling methods including artificial intelligence algorithms, artificial neural networks (ANN), evolutionary algorithms (EA), fuzzy logic (FL), immune systems (IS), ant algorithms (AA) and artificial life algorithms (ALA), etc. [2-3, 5-6, 9-10, 12-15, 18-28]. Neural modelling, based on ANN, involves development of an ANN and teaching it an EP system development model based on previously measured input and output quantities contained in the training and test files [5, 10, 12, 15-23, 25-27].

1.2. Areas of neural modelling of the EP system development

Areas of neural modelling of the EP system include, i.a., supporting neural modelling, training and improvement of the system as well as EPS operation. Each area has specific programming environments and methods to design and train the ANN. The areas distinguished in Fig. 1 were developed taking MATLAB and Simulink environment into account.

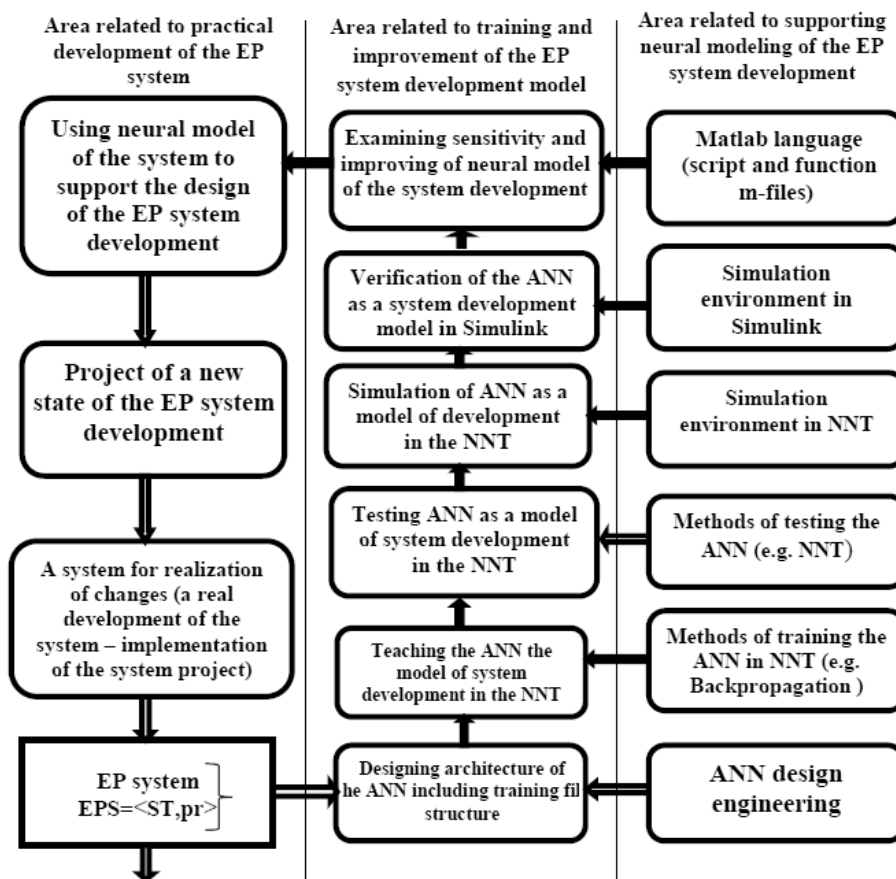


Fig. 1. General block diagram presenting neural modelling of the EP system development. Denotations: ST – structure of the EP system, pr – process of power and electrical energy transmission in the EPS. The remaining denotations in the text. Source: [26]

Therefore, appropriate libraries and Matlab language were distinguished in the area of supporting modelling. The lowest level of neural modelling is connected with the systemic approach to designing architecture of the ANN as well as training and test files. Literature on the subject lacks well worked out

methods of preparing research experiment, including the structure of training and test files for the model of the EP system development.

Therefore, developers usually use software engineering, and related methods and development procedures. In this respect, libraries offered by programs offered by MATLAB and Simulink environment, in particular, Neural Network Toolbox (NNT) and Fuzzy Logic Toolbox (FLT), as well as Control System Toolbox (CST) and System Identification Toolbox (SIT) proved especially useful.

The next level of neural modelling is the level that involves training the model of the system, which, in the MATLAB and Simulink environment may be realized with the help of the above mentioned libraries NNT and FLB, as well as other toolboxes such as SIT or CST and Matlab language. Various methods of training may be applied, including backpropagation, which is the most commonly used method.

However, there are no methods oriented towards systems of system development. There are no methods of selection of the number of neurons in each layer of the ANN, i.e. in the input and output layers as well as hidden layers, the number of hidden layers and the selection of activation function, etc. with consideration to the nature of the real system being modelled.

2. Designing and training the ANN on the EPS development model

2.1. Preparation of numerical data for the purpose of training the ANN

Selection of the ANN architecture and the method of training in the case being discussed depend on the nature of the EP system development.

In order to conduct research experiments, training and test data were prepared using numerical data related to the first area of the IEEE RTS 96¹ test system (see Figure 2), which consists of 73 nodes, 120 branches and 96 generation units, with the total power of 10 215 MW [1, 8, 11, 24].

It consists of 16 input quantities (u_i) and 3 output quantities (y_j), described in detail in table 1. Graphs of input quantities of the EP system determined based on the values of the IEEE RTS 96 test system is placed in Table 2.

In the diagram of connections between generating and receiving nodes and parameters of each generating node and receiving node, parameters of balancing nodes located between initial and end node were treated as common parameters – Table 3. In order to obtain data for the research experiment, lengths of all connections between nodes that constituted a conventional generating-receiving node, were summed up, and parameters connected with appropriate nodes on the routes of connections were averaged.

¹ The initial version of the RTS system (RTS 79) consisted of only one area. In 1986 data were supplemented, and, the new system, i.e. RTS 79/86 consisted of 38 branches and 24 nodes. However, the system was not complex enough, which resulted in the decision to develop a newer version of the system, namely, RTS 96.

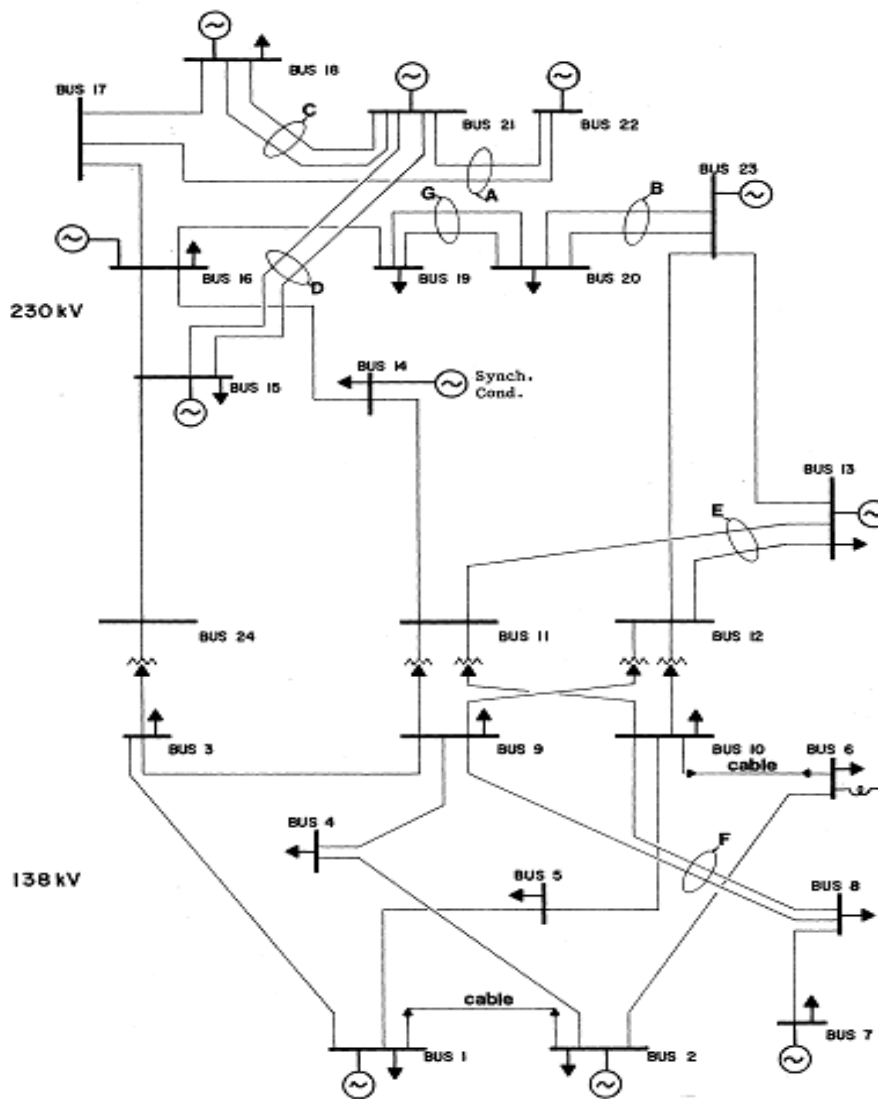


Fig. 2. A diagram of the RTS-78/86 system in one area of the RTS-96 system. Denotations: Bus - node (possible types: generating, receiving, balancing), **A, B, ..., G** - lines that have common buses (or posts), ⊗ - generating power. Remaining denotations in the text.
Source: [1, 8, 11-12, 24, 27]

Numerical data prepared using the above mentioned were normalized, and, in the form of matrices (matrix of input quantities and matrix of output quantities) were imported to the MATLAB Workspace.

Files containing training data were used during training the ANN, while the test file was used to verify the reaction of the ANN to the selected input functions. Normalization of input and output quantities was conducted in accordance with the following formula:

$$u_{ni} = \frac{u_i}{\sum_{i=1}^n u_i} \quad (1)$$

where: u_i – i -th input quantity, n – number of input quantities (here: $n = 16$).

Table 1. Information related to output quantities. Source: [11-12, 24, 27]

No.	Input	Type of data	Unit	Description
1	u_1	L	[km]	Length of line
2	u_2	λ_p	[1/a]	Frequency of continuous interferences
3	u_3	Dur	[h]	Duration of continuous interference
4	u_4	λ_t	[1/a]	Frequency of transient interferences
5	u_5	R	[pu]	Branch impedance
6	u_6	X	[pu]	Branch impedance
7	u_7	B	[pu]	Shunt susceptance
8	u_8	Con	[MVA]	Continuous current-carrying capacity
9	u_9	LTE	[MVA]	Long-term emergency current-carrying capacity
10	u_{10}	STE	[MVA]	Short-term emergency current-carrying capacity
11	u_{11}	Type of unit	[MW]	Maximum power of the generating unit
12	u_{12}	P_G	[MW]	Active (real) power
13	u_{13}	Q_G	[Mvar]	Reactive power
14	u_{14}	Q_{max}	[Mvar]	Maximum limit of reactive power
15	u_{15}	Q_{min}	[Mvar]	Minimum limit of reactive power
16	u_{16}	V_S	[pu]	Voltage applied to the node of the generator
17	y_1	P	[MW]	Active load
18	y_2	Q	[MVA]	Reactive load
19	y_3	U	[kV]	Voltage rating

Normalized values of quantities determiner for the purpose of training were saved in the MATLAB Workspace as matrices with the dimensions 16x60 for input quantities and with the dimensions of 16x3 for output quantities. They were obtained as averages for individual nodes used in the research experiment. This allowed to obtain 60 values that characterized parameters of 60 nodes (specific replacement quantities).

Table 2. Graphs of input quantities of the EP system determined based on the values of the IEEE RTS 96 test system. Denotations: axis x – training time, axis y – values of output quantities. Source: Author’s own compilation based on [1, 8, 11-12, 24, 27]

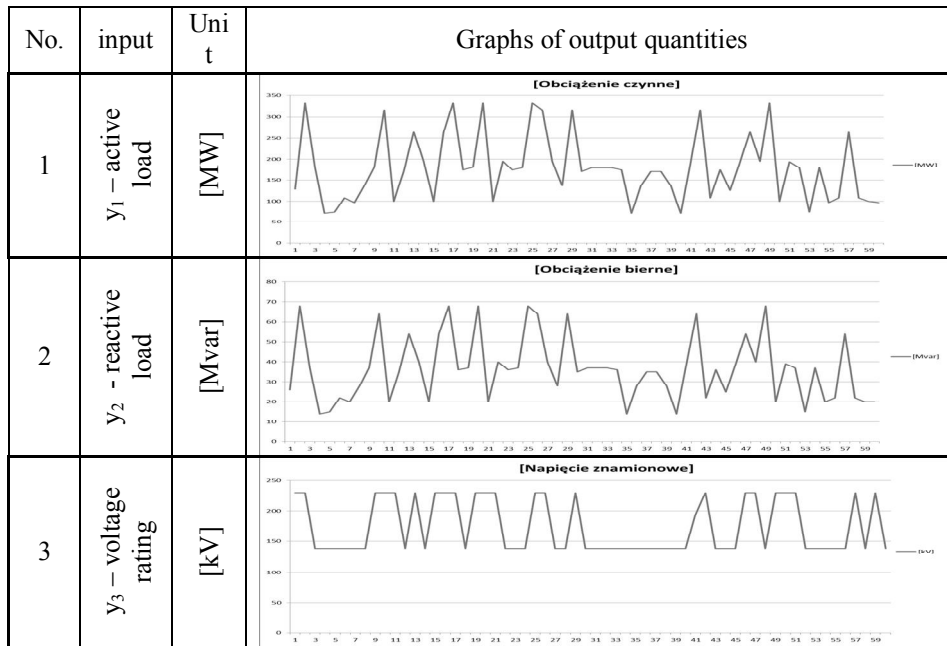


Table 3. Example of determination of input quantities and output quantities values (training and test files) for the purpose of teaching the ANN the model of the EPS system development. Source: [1, 8, 11-12, 24, 27]

No of nodes	No	From node	To node	L	λ_p	Dur	λ_t	R	X	B	Con	LTE	STE	No of node	Type of generator unit	P_G	Q_G	Q^{max}	Q^{min}	V_S	Load	Voltage rating	
piece	-	-	-	km	1/a	h	1/a	pu	pu	MVA	MVA	MVA	No	u	MVar	MVar	MVar	MVar	pu	MW	MVar	kV	
-	-	101	105	35,41	0,33	10	1,2	0,022	0,085	0,023	175	208	220	101	48	43	7,05	20	12,5	1,03	*	*	*
-	-	105	110	37,01	0,34	10	1,2	0,023	0,088	0,024	175	208	220	-	-	-	-	-	-	-	*	*	*
-	-	106	110	25,75	0,33	35	0	0,014	0,061	2,459	175	193	200	-	-	-	-	-	-	-	-	-	-
3	28	101	106	98,17	1	18,3	2,4	0,059	0,234	2,506	175	203	213,3	101	48	43	7,05	20	12,5	1,03	136	28	138

2.2. Designing ANN using NNT

Neural Network Toolbox was used to design the ANN. For the purpose of conducting research experiments two structures of the ANN were selected, i.e. Cascade-Forward Backpropagation and Feed Forward Backpropagation, using the backpropagation method, based on computing the error the ANN makes in the

direction reverse to the flow of information, i.e. from the output layer to the input layer. In order to obtain optimal results of teaching the ANN the model of the EP system development, sensitivity of the ANN to changes of parameters of the following types: activation function, training function, architecture, learning rule, number of layers, number of neurons in the hidden layer, etc. was examined.

2.3. Teaching ANN the model of the EPS development

As a result of teaching the ANN with the number of neurons in the input layer corresponding to the number of rows of the input matrix and with the number of neurons in the output layer corresponding to the number of rows of the output matrix, the following graphs were obtained, see Figure 3.

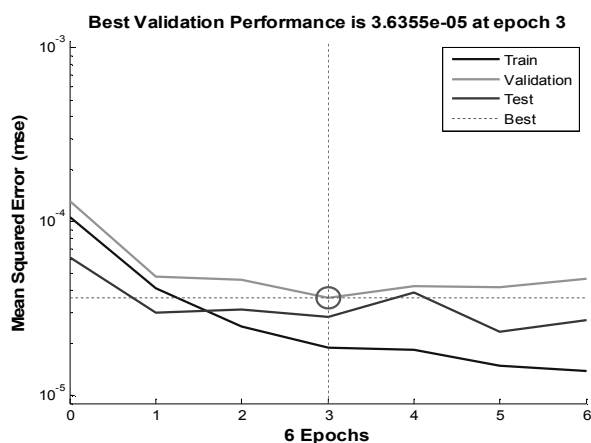


Fig. 3. An example graph of train error, test error and validation error. Denotations in the text: Epochs – train epochs, Mean Squared Error, Train – graph of train error, Validation – graph of validation error, Test – graph of test error, Best – the best result. Source: [12, 27]

Train error fell by one order of magnitude after 6 epochs, with testing and validation having little impact on the results of learning. In order to examine sensitivity of the ANN, 15 research experiments were conducted, connected with changes of such parameters as: number of hidden layers, number of neurons in each hidden layer, activation function, learning rule, etc. As a result of training, a catalogue of models was obtained. Selected models are presented in Table 4.

The best results were obtained for the ANN with one hidden layer that consisted of 10 neurons, for which architecture the train error reached the accuracy of 10^{-5} after only six epochs for some ANNs (see Figure 4).

Out of 15 designed ANNs, the best results were obtained for IEEEnModel11 with one hidden layer that consisted of 10 neurons, tansig activation function, feed-forward backprop network type, and TRAINLM training function.

Table 4. Parameters of the network, graphs of learning curve, and output values of the network, following comparison with the output training values. Source: [12, 27]

Parameters of the network: IEEEEnModel11. Number of neurons: 10; Number of layers: 2; Activation function: Tansig; Type of network: Feed-forward backpropagation, Train function: TRAINLM	
	Denotations: Epochs - train epochs, Mean Squared Error, Train – graph of train error, Validation – graph of validation error, Test – graph of test error, Best – the best result
	Scope5 – The accuracy of generated voltage rating [kV] by the neural model of the EPS as related to voltage rating of the real system
	Scope6 – The accuracy of the generated active load [MW] by the neural model of the EPS as related to the active load of the real system
	Scope7 - The accuracy of the generated reactive load [Mvar] by the neural model of the EPS as related to the reactive load of the real system

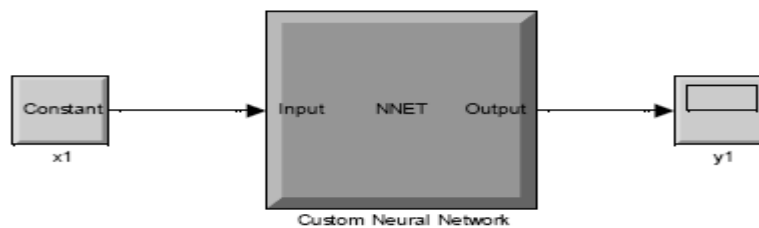


Fig. 4. A generate model of the ANN. Denotations: x_1 – input signals, y_1 – output signals generated by the network, input – input of the ANN, nnet – ANN, output – output of the ANN. Source: [12, 27]

Graphs in Table 4 present the process of training the ANN for which the best results were obtained. However, the accuracy of the obtained graphs at the output of the ANN in comparison with the IEEE RTS test data, i.e. active power, reactive power, and voltage rating is shown in Table 5.

Table 5. Graphs of errors of ANNs that were trained on selected models of the EP system based on the IEEE RTS test data. Denotations in the text. Source: Author's own compilation based on the results of research presented in work [12]

Name	Graphs of errors of the neural models outputs in comparison to the IEEE RTS test system
IEEEEnModel11	
IEEEEnModel15	
IEEEEnModel10	
IEEEEnModel15	

3. Analysis of research results

The ANNs, trained on the EP system development model based on the IEEE RTS test data, were used in the comparative studies related to the IEEE RTS test model.

Individual outputs of the models were compared with their respective outputs of the EP systems in order to find the graphs for the smallest errors generated, using the following formula:

$$y_i = \frac{(y_{SNNi} - y_{SEEi})}{y_{SEEi}} \quad (2)$$

where: y_i – value of i-th error quantity at the output, y_{SNNi} – value of i-th output of the ANN, y_{SEEi} – value of i-th output of the IEEE RTS test system.

As a result of the process of teaching the ANN the model of the IEE RTS system, weight matrices of two layers were obtained, which layers assumed values presented in Table 6 and Table 7 for the input and hidden layers respectively, for IEEEEnModel11.

Table 6. Values of weights of the input layer. Source: [12, 27]

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	-0.6883	0.5084	0.1144	-0.0786	0.4233	-0.0247	-0.5433	0.6347	-0.7055	-0.5111	-0.1275	-0.4187	-0.0861	0.1959	-0.3702	0.1492
2	-0.4683	0.5306	-0.9460	-0.0837	-0.5486	0.3253	-0.6666	-0.5686	0.4462	0.5059	0.2486	0.3567	3.7475e-05	0.3106	0.1666	-0.6172
3	0.3805	0.7943	0.3134	0.0316	-0.5427	0.4933	0.3851	-0.2169	-0.1929	-0.7397	0.1591	0.3791	0.5724	-0.0470	-0.4152	-0.0801
4	-0.5439	-0.3450	0.0754	0.3537	-0.4376	0.6441	0.4342	-0.2795	-0.6763	-0.4612	0.6059	-0.2669	-0.4186	0.5090	0.3385	-0.0735
5	0.5095	0.0279	0.3002	0.2459	-0.7456	-0.5683	-0.2179	0.0992	-0.1058	-0.5288	-0.3563	0.4366	-0.1498	0.0641	0.4371	0.6780
6	0.2229	-0.4958	0.4592	0.4291	-0.4074	0.2769	0.0210	0.3736	0.1611	0.1471	0.1976	-0.1129	-0.7253	1.0641	-0.4444	1.0878
7	-0.2288	-0.4613	0.3954	-0.2310	-0.2010	-0.4918	0.5014	-0.6723	-0.9195	-0.1488	-0.6044	0.5484	0.7246	0.1911	0.7649	-0.3280
8	-0.0495	-0.1751	-0.4036	-0.0336	0.2463	0.3126	-0.6645	0.5746	0.5213	0.2789	-0.1771	0.5021	0.4711	-0.8061	0.0502	0.5503
9	0.2338	-0.4912	-0.8862	-0.5969	-0.0407	0.3161	0.3404	-0.0249	-0.4217	-0.1501	0.3377	-0.2263	0.1689	-0.6278	-0.4841	0.4090
10	-0.2246	-0.1589	-0.0347	0.4278	0.8039	-0.2822	0.2842	-0.4040	0.7749	0.3875	0.1153	0.4162	0.4084	-0.3676	-0.0790	0.0208

Table 7. Values of weights of the hidden layer. Source: [12, 27]

	1	2	3	4	5	6	7	8	9	10
1	-0.7182	-0.8177	-0.2707	-0.5702	-0.0350	-0.6926	-0.3336	0.2772	0.2086	0.2543
2	-0.5473	-0.8045	-0.4987	-0.2800	-0.1835	-0.6788	-0.3738	0.5255	0.1282	-0.4895
3	-0.3042	0.2112	0.8398	-0.5774	-0.2817	-0.1548	0.7258	0.0588	0.3435	-0.2572

4. Designing a simulation model

A model of EP system development for simulation research was designed in Simulink. The main block of the model is an Artificial Neural Network (ANN), trained on the model of the EP test system in the MATLAB and Simulink environment using the NNT. A block diagram of the ANN is shown in Figure 5.

Such a block diagram of the neural model may be used for simulation research and for examining sensitivity (Figure 6).

As it may be observed, input variables based on IEEE RTS test data were fed to the input of the ANN block of the block diagram in Simulink. Values of output variables of the ANN were compared with the values of output variables based on the IEEE RTS test data.

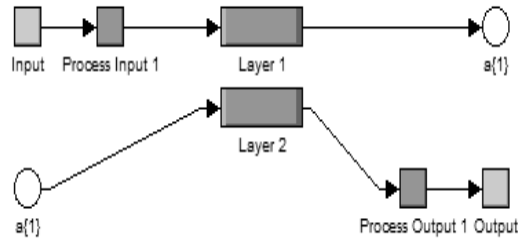


Fig. 5. A block diagram of the structure of the neural network model. Denotations in the text. Source: MATLAB package. Denotations: Process Input 1: weights for the first layer, Layer 1: first hidden layer, $a\{1\}$: output of the hidden layer, Layer 2: the second layer, Process Output 1: weights for the second layer. Source: [12, 27]

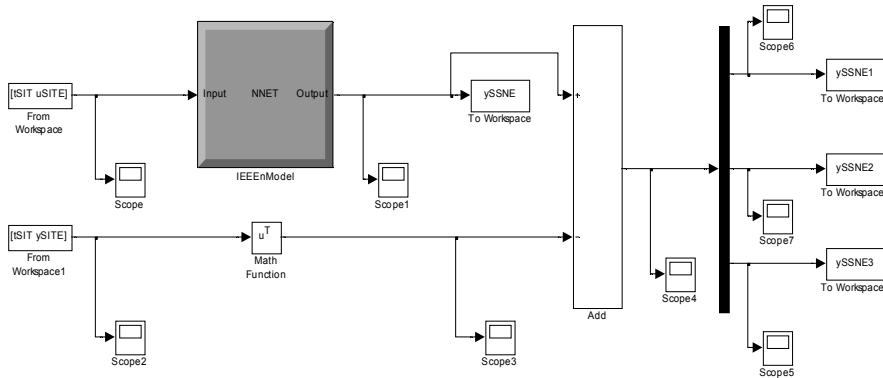


Fig. 6. A view of the model designed in Simulink. Denotations: NNET – a model of EPS development, From Workspace – importing data from MATLAB workspace, To Workspace – transferring results of calculations to MATLAB workspace, Math Function – transposition of a matrix, Scope – visualization of results. Source: [12, 27]

A Demux block was used to import output variables from the ANN output vector. Their graphs are presented in Figure 7 (active power), Figure 8 (reactive power) and Figure 9 (voltage rating).

By comparing the graphs of output variables of the ANN with the graphs of appropriate output variables of the IEEE RTS model it is possible to analyse the discrepancies between them. It may be observed that the obtained graphs of differences between the signals indicate high accuracy of reactions of the ANN to the input values fed.

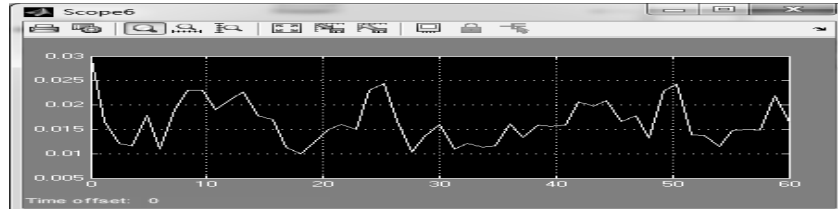


Fig. 7. A graph of *active power* values generated by the ANN. Source: [12, 27]

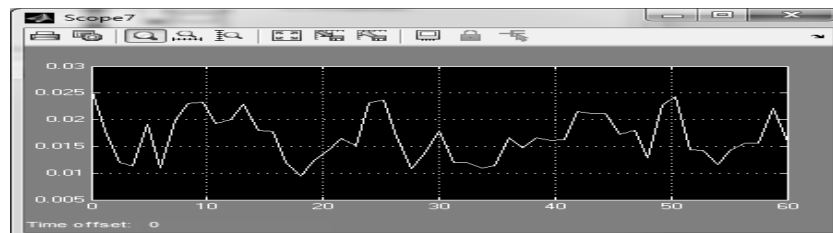


Fig. 8. A graph of *reactive power* values generated by the ANN. Source: [12, 27]

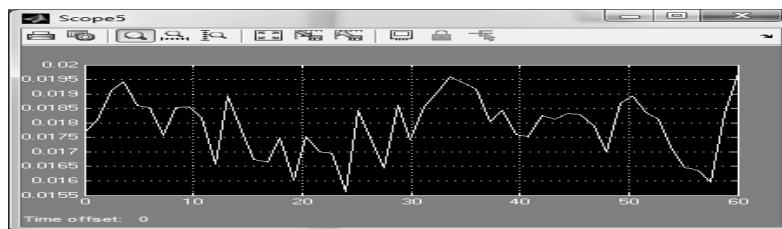


Fig. 9. A graph of *voltage rating* values generated by the ANN. Source: [12, 27]

5. Conclusions

Apart from analytical and identification modelling, neural modelling methods are also being developed. However, neural design engineering of the EP system development and methods of training and testing models of development are not well developed.

As a result of designing and training the ANN, models of the EPS development were obtained using IEEE RTS data, which were subjected to simulation research and sensitivity examinations, i.a. to changes of the number of hidden layers and number of neurons in a layer.

Designing and training the ANN requires determination of appropriately selected (considering the phenomenon being modelled) input quantities and output quantities, as well as, i.a. activation function and learning rule. At the end, a neural model is the EPS model of development, composed of an adder of products of weight matrices and input values as well as an activation function with the above mentioned adder as an independent variable.

Sensitivity examinations of the model of development indicate that both parameters and the structure of the neural model of the EP system may be refined. The obtained models were especially sensitive to the change of the number of hidden layers, number of neurons in a layer and activation function.

The best ANN used for designing and training the model of the EP system was a Backpropagation network. The obtained model of the EP system was used for simulation research in Simulink. The ANN as a model of the EP system development proved to respond to excitations with high accuracy compared to the output variables of the IEEE RTS test system.

In further research concerning neural modelling of the electrical power system, it is worth considering the possibility of developing systems correcting models of system development in the form of ANN, which requires, i.a. conducting detailed research on sensitivity and developing a method of synthesis of artificial neural networks by analogy to synthesis of electronic systems.

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