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The Influence of the Artificial Neural Network type on the quality of learning on the Day-Ahead Market model at Polish Power Exchange joint-stock company

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Abstract. The work contains the results of the Day-Ahead Market modeling research at Polish Power Exchange taking into account the numerical data on the supplied and sold electricity in selected time intervals from the entire period of its operation (from July 2002 to June 2019). Market modeling was carried out based on three Artificial Neural Network models, ie: Perceptron Artificial Neural Network, Recursive Artificial Neural Network, and Radial Artificial Neural Network. The examined period of the Day-Ahead Market operation on the Polish Power Exchange was divided into sub-periods of various lengths, from one month, a quarter, a half a year to the entire period of the market's operation. As a result of neural modeling, 1,191 models of the Market system were obtained, which were assessed according to the criterion of the least error MSE and the determination index R2.

Keywords. Perceptron Artificial Neural Network, Radial Artificial Neural Network, Recursive Artificial Neural Network, neural model quality, Day-Ahead Market, Polish Power Exchange, Mean square error, determination index.

1. Introduction

Artificial Neural Networks (ANNs) are considered to be computational models inspired by solutions of biology and biocybernetics modeled on the functioning of the nervous system in particular the human brain [16-19]. There are many types of artificial neural networks such as Percepton ANNs, Recursive ANNs, Cellular ANNs, etc. [2, 5, 6-9, 17-18, 24], and new ANNs are constantly being created as a result of both modifications of the existing ones, as well as completely new concepts, such as Ontogenic ANNs, Chaotic ANNs, Developing ANNs or recently Deep ANNs [3-4, 11, 23].

All ANN models are implemented on the basis of a weighted adder on each neuron (sums of the products of input signals and weights) and based on the function of the activation of neurons selected for the specificity of the problem being solved [2, 5, 7, 8, 24], as well as a set of operations performed on these models, which are most often operations in the vector-matrix space performed on real numbers resulting from the ANN learning rule or from the vector-matrix calculus dictated by the determination of output signals as a result of ANN operation [2, 10, 12, 24]. ANNs are often used to build models of neural systems, e.g. for the purposes of studying the behavior of the system, e.g. as a result of forecasting, or classification or pattern recognition 10, 24], as well as the use of ANN to model neural prices on the Day-Ahead Market (DAM) of the Polish Power Exchange (PPE) [12].

2. Formulation of the research problem

The essence of the research problem presented in this paper concerns the examination of the impact of the selected three models (ANN), i.e. Perceptron ANN, Radial ANN, and Recursive ANN, on the quality of the obtained neural model of the Day-Ahead Market using the numerical data listed on PPE [12].

They are works which presents researches on DAM models for price forecasts [9] but they analyses different aspects for example: hourly series records of recent prices, power demands, power generations into the previous day weather to find the best DAM model.

It was assumed that the main goal of the research is to search for the quality of the mapping of the above three DAM neural models as a multidimensional approximation of the relevant ANN. Due to the relatively large set of learning and testing pairs used to teach ANN, i.e. pairs built on the basis of the data from the years 2002-2019, an approximation is made in the ANN learning process using the least-squares method.

The selected models have been implemented and tested for various time periods from the period of operation of the DAM at PPE, starting from a monthly period, through a quarter, half-year, three quarters, one year, 2 years, up to 15 years, and for the entire period of the above-mentioned period (from July 2002 to June 2019).

An additional goal is to show that the number of teaching and testing pairs depends primarily on the specificity and properties of the DAM system at PPE, and thus depends on the quality and quantity of teaching and testing data.

Therefore, the paper shows, in addition to the obtained results of the Perceptron ANN learning research, the impact of the number and quality of teaching and testing pairs taken from the DAM at PPE on the quality of the neural model. The research was carried out in the MATLAB and Simulink environment with the use of our own m-file library [1, 12].

As a measure of the quality of the model, determination factor (R^2) and mean square error (MSE) was taken. It was assumed, among others, that the model is considered correctly learned for a given number of training pairs and testing pairs, if the value of R^2 and the mean square error MSE do not differ more than the permissible error from the highest value of R^2 and the smallest MSE value obtained for all the tested models.

The work is a continuation of the author's earlier works, which show, among others, numerical data used in research experiments, details of the design and implementation of the Perceptron ANN and the results of the analysis of neural identification, including evolutionary support for improving ANN parameters [12-16].

Moreover, the works [21, 22] show the detailed purpose of the DAM neural modeling, which is not only the search for the DAM neural model necessary to forecast prices by both consumers or electricity suppliers purchasing on the DAM, but also for the DAM system conducting transactions on the one hand and to build a research base to improve the accuracy of the neural model using methods inspired by quantum computing on the other hand.

3. Artificial Perceptron Neural Network

Perceptron ANN is the oldest and not fully used ANN architecture to this day (Fig. 1), and especially its modified version using the sigmoid activation function, ie the logistic function or the hyperbolic tangent [12]. This ANN carries out calculations based on successive weighting layers, in which the input data is converted into the output data, and the calculation process only takes place in one direction (forward).

On the other hand, the ANN learning process, i.e. weight correction, takes place in the opposite direction as a result of the so-called error back propagation, which is based on minimizing the error determined on individual layers of neurons from the last layer to the first layer using the method of the highest error decrease.

This type of ANN usually has several layers of neurons, so it consists of an input layer, an output layer and from one to several hidden layers. The learning results of the Perceptron ANN were included, in works [12-13].

4. Radial Artificial Neural Network

A radial ANN is basically a two-layer ANN, in which a radial function is performed in the first layer, and a classic Perceptron with a linear function of neuron activation is realized in the second layer (at the same time the output one). The main difference between the classic Perceptron ANN and the Radial ANN are the operations performed in the input layer, where instead of the classic neuron activation function, which is most often the tansig function with the net argument being the sum of the weighted values of the input vector, a radial function (e.g. radbas) is used.

The net argument uses the products of the modulus of the value difference between the input vector value and the weight value, and possibly the signal shift value [10, 18, 24]:

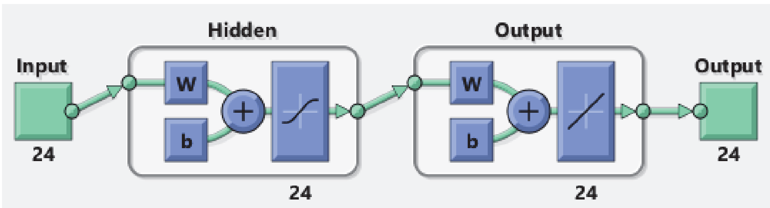


Figure 1. Architecture of the Perceptron ANN taught in the DAM neural model. Markings: Input (24) - input signals to ANN, here: volume of electricity supplied and sold in each hour of the day (24 signals), Hidden - hidden layer model in which the weight matrix (W) and the biase vector (b) are distinguished, Output - model of the output layer, in which the weight matrix (W) and the biase vector (b) are also distinguished, Output (24) - output signals from ANN (24 signals, here the average price obtained on the exchange in a given hour of the day, weighted by the volume of energy sold. Source: Own elaboration with the use of MATLAB and Simulink environment [1].

$$y_i^1 = \text{radbas}(||u_j - w_{ij}||b_j) \tag{1}$$

where:

y_i^1 – i-th output signal (on i-th neuron of the output layer),

u_j – j-th input signal (on j-th neuron of the input layer),

w_{ij} – weight between the i-th output and the j-th input (j-th neuron of the input layer and the i-th neuron of the output layer),

b_j – j-th bias signal on input layer.

The most frequently used function of activating neurons, i.e. the radbas function, is as follows:

$$\mathrm{radbas(net)} = e^{-net^2}, \tag{2}$$

where:

net – weighted input adder

$$net = \sum y_i^1. \tag{3}$$

As equation (2) shows, the radbas () function reaches its maximum of one when net = 0, i.e. when the difference between the input data and the weights is zero. The next ANN layer is the output layer, which is a classic Perceptron ANN layer, in this case with the function of activating *purelin* neurons.

There are several versions of Radial ANN depending on their use, e.g. implemented through the newrbe (Exact Radial Basis Network), newrb (Radial Basis Network), newpnn (Probabilistic Neural Network) or newgrn (Generalized Regression Neural Networks, GRNN) functions, whose functioning has been described in more detail, among others at work [1]. Radial ANN of GRNN type (Fig. 2) was used for further research due to its ability to approximation. Its characteristic feature is that the output values from the first layer of neurons, before entering the second layer of neurons, are additionally processed by the *normprod* function, which is the product of the output signal $\mathbf{y^1}$ and the second layer weight matrix $\mathbf{w^2}$ normalized by the sum of the vector elements $\mathbf{y^1}$, the individual neuronal signals can be expressed as follows:

$$normprod(y'_j) = w_{ij}^2 * y_j^1 / \sum y_j^1 \tag{4}$$

where:

y'_j – normalized output from the first layer of neurons.

5. Recursive Artificial Neural Network

Recursive ANN works by saving the output data from the layer and transmitting them in feedback to the neurons of the input layer so as to strengthen the signal processing process in the input layer and stabilize the operation of the entire ANN (Figure 3). The first layer is created similarly to the Perceptron Artificial Neural Network with the adder of weighted products of the input vector values. In contrast, the output from layer one in step t goes as input to this layer in step t + 1. From the point of view of the control theory and systems, it is believed that Recursive ANNs are nonlinear dynamic systems, hence they are used in processes with data not only current, but also from the past [5, 10, 24].

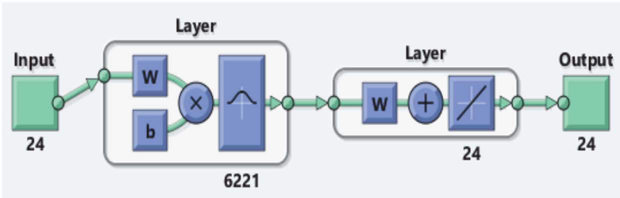


Figure 2. Architecture of the Radial ANN used in the research experiment. Markings: Input (24) - input signals to ANN, here: 24 signals being the volume of electricity sold in each hour of the day, Layer (6221) - input layer consisting of 6221 neurons with a radial function of neuron activation (each input signal is represented by another neuron), Layer (24) - the output layer of neurons consisting of 24 output neurons with a linear function of neuron activation, Output (24) - output signals from ANN (here: 24 signals being the average price weighted by the volume of electricity sold in each hour of the day. Source: Own elaboration in the environment of MATLAB and Simulink [1].

This paper presents a two-layer network with a feedback delayed by one cycle with the signal in the first layer, the activation function of the first *tansig* layer, i.e. the classic Elman network, which, next to the ANNs of Hopfield, RTRN, Hamming and BAM, is also classified as ANN that can also be used as associative memories [17] due to the fact that the sequential learning process of a Recursive ANN means that from the first step to the next each neuron will remember some information it had in the previous time step.

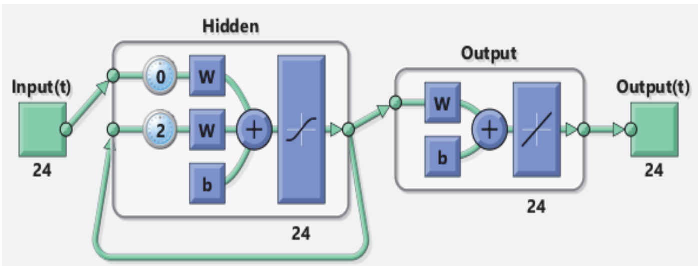


Figure 3. Architecture of the Recursive ANN. Symbols: Input (t) (24) - input signals to ANN, here: volume of electricity supplied and sold in each hour of the day (24 signals), Hidden - hidden layer model in which the weight matrix (W), which is processed, is distinguished by two input vectors at time t (0) and the output from the hidden layer from time (t2) i.e .: product of the weight matrix (W) with the input vector at time t (0), product of the weight matrix (W) with the output vector from the layer hidden at time t (2), the so-called feedback and bias vector (b), Output - output layer model, in which the weight matrix (W) and bias vector (b) are also distinguished, Output (24) - output signals from ANN (24 signals, here the average price obtained on the exchange in a given hour of the day, weighted by the volume of electricity sold Source: Own study in MATLAB and Simulink environment [1].

This architecture makes each neuron act as a memory cell while performing calculations. In the case of the erroneous value stored in the previous step, it is corrected by the learning or coefficient error correction. This process being characteristic also for ANN learning with backward error propagation.

6. Description of the conducted experiment

In the case under consideration, the PPE of the Day-Ahead Market system is modeled using three types of ANN architecture with parameters shown in Table 1. Data for ANN training and testing were collected from the DAM from the entire period of PPE operation, i.e. from 01/07/2002 to 30/06/2019. [25].

This period was divided into time intervals with different lengths of measurement samples, distinguishing the teaching and testing pairs, as shown in Table 2, i.e. month, quarter, half-year, year, 2 years, 3 years, 4 years, 5 years, 6 years with a step of 1 year, 7 years with a step of 1 year, 8 years with a step of 1 year, 9 years with a step of 1 year, 10 years with a step of 1 year, 15 years with a step of 1 year and the entire period under study, i.e. from 01.07. 2002 to 30.06.2019.

Table 1. Use of various types of Artificial Neural Networks as DAM neural models. Source: Own study in the MATLAB and Simulink environment [1].

Parametr	**Artificial Perceptron Neural Network**	**Artificial Recurent Neural Network**	**Artificial Radial Neural Network**
Number of layers	2	2	2
The number of neurons in the hidden layer	24	24	depending on the number of input vectors (from 30 to 6 221)
The number of neurons in the output layer	24	24	24
First layer transformation function	tansig	tansig	radbas
Second layer transformation function	purelin	purelin	purelin
Rating function	MSE	MSE	MSE

The result of learning ANN are neural models in the form of a substitute diagram of the DAM system. Learning the ANN model of the neural market system required preliminary data preparation (e.g. their normalization), i.e. both input quantities (u) for 24 variables being the volume of electricity supplied and sold in particular hours of the day expressed in [MWh], as well as input (y) concerning 24 variables being the weighted average of prices obtained in particular hours of the day for the supplied and sold electricity, expressed in [PLN / MWh]. The studied data sets were trained in the MATLAB and Simulink environment on selected - as already mentioned above - three types of neural networks, ie Perceptron ANN, Radial ANN and Recursive ANN [1].

Table 2. Possibilities of training ANN with the use of data from periods of different possible lengths of quotations on the PPE DAM. Source: Own study in the environment of MATLAB and Simulink [1].

Period	**Number of learning subsets**
month	204
quarter	68
half-year	34
year	17

2 years	8
3 years	5
Four years	4
5 years	3
6 years in steps of 1 year	12
7 years in steps of 1 year	11
8 years in steps of 1 year	10
9 years in steps of 1 year	9
10 years in steps of 1 year	8
15 with steps of 1 year	3
the entire period under study, i.e. 01/07/2002 - 30/06/2019	1

Quotations on the PPE DAM are held daily, and the contracts are concluded 24 or 48 hours before the electricity is delivered to the recipient, and they are concluded for specific hours according to a specific schedule, where each of the participants of PPE join-stock company has its own account (wallet) and can place any number of orders. Each order specifies, inter alia, the code of the forward instrument of the given type of order, type of order (purchase or sale), portfolio for which the order is placed, volume (amount of energy purchased or sold), etc. Information about transactions is published on the website of PPE and they were the source of data for the conducted analysis described in more detail in [12].

The purpose of this additional experiment was to check how and to what extent individual ANN types, i.e. Perceptron, Recursive and Radial, enable to obtain a neural model of the DAM system for individual periods distinguished in Table 2.

Therefore, individual data sets (the same) were used. for learning and testing the above-mentioned three types of ANN. As a result of the conducted experiments, 397 models of the PPE Day-Ahead Market system were obtained for different time periods for one type of ANN, i.e. a total of 1,191 models were obtained.

The mean square error MSE and the coefficient of determination R^2 were used as the evaluation criteria for each model obtained. Selected research results concerning the teaching of the above-mentioned three different types of ANN obtained for the consecutive periods in Table 2 are presented in the following tables, i.e. in Table 3 - for Perceptron ANN, in Table 4 - for Recursive ANN and in Table 5 - for Radial ANN.

Table 3. Modeling results for the MSE error value obtained for the Perceptron ANN. Source: Own study in the environment of MATLAB and Simulink [1].

The length of the quotation period on the PPE DAM	**The obtained MSE values for the appropriate length of modeling periods**			**The obtained R^2 values for the appropriate length of modeling periods**		
	max	**min**	**mean**	**max**	**min**	**mean**
month	0,031538	9,46E-09	0,000957	0,910676	0,13284	0,671464
quarter	0,010239	6,39E-05	0,001033	0,883035	0,260872	0,664489
half a year	0,006723	0,000252	0,001065	0,798673	0,330543	0,622812

3 quarters	0,004574	0,000316	0,001325	0,847599	0,20746	0,622259
year	0,004898	0,000334	0,00144	0,787481	0,395959	0,60331
2 years	0,003954	0,000434	0,001577	0,74061	0,46056	0,567373
3 years	0,002339	0,000631	0,00115	0,655004	0,492299	0,5669
Four years	0,003568	0,000549	0,00158	0,662723	0,467276	0,545216
5 years	0,00238	0,000578	0,001387	0,560887	0,516093	0,539543
6 years (step)	0,003291	0,000706	0,001495	0,654797	0,368147	0,533565
7 years (step)	0,002478	0,000868	0,001524	0,638559	0,462133	0,536493
8 years (step)	0,002173	0,000824	0,001462	0,641572	0,434553	0,516764
9 years (step)	0,002372	0,000876	0,001556	0,577501	0,437375	0,507126
10 years (step)	0,002316	0,000931	0,001616	0,537034	0,472314	0,501819
15 years (step)	0,00205	0,00179	0,00193	0,484907	0,442602	0,45778
Entire period (10 trials)	0,00192	0,001749	0,001838	0,474964	0,411678	0,446714

Based on the research results obtained, incl. presented in Table 3, it is possible to assess both the value of the obtained measures and their consistency. For Perceptron ANN, the greatest fluctuations of both MSE and R^2 are characteristic for shorter time intervals, while in the case of longer time intervals these results are more stable, i.e. in the sense of obtaining a smaller difference between the maximum, minimum and average values, while the values of the obtained indicators MSE and R^2 are better over shorter time frames.

Table 4. Modeling results for the MSE error value obtained for the Recursive ANN. Source: own study in the MATLAB and Simulink environment [1].

The length of the quotation period on the PPE DAM	The obtained MSE values for the appropriate length of modeling periods			The obtained R^2 values for the appropriate length of modeling periods		
	max	**min**	**mean**	**max**	**min**	**mean**
month	0,031537658	9,46E-09	0,00095710	0,961400642	0,107221227	0,68269362
quarter	0,010239491	6,39E-05	0,00103264	0,879315101	0,327450804	0,686017791
half a year	0,00672258	0,00025243	0,00106481	0,857767872	0,421374546	0,631611484
3 quarters	0,004573517	0,00031592	0,00132514	0,802034954	0,351324368	0,610984967
year	0,004898169	0,00033368	0,00144031	0,744186821	0,394576997	0,585496245
2 years	0,003953986	0,00043353	0,00157741	0,751684855	0,499358024	0,581466843
3 years	0,002339183	0,00063104	0,00115047	0,689484802	0,496569148	0,598435443
Four years	0,003568284	0,00054876	0,00157986	0,673003697	0,362276643	0,548484123
5 years	0,0023804	0,00057758	0,00138650	0,607249548	0,492258384	0,541968976
6 years (step)	0,003291003	0,00070601	0,00149452	0,644599414	0,398191691	0,536592361
7 years (step)	0,002477605	0,00086815	0,00152385	0,658084844	0,403168211	0,528797511
8 years (step)	0,002172731	0,00082442	0,00146249	0,669648345	0,454501106	0,538544581
9 years (step)	0,002372093	0,00087583	0,00155602	0,580174575	0,47053065	0,516994827
10 years (step)	0,002315695	0,00093072	0,00161563	0,561239796	0,438692143	0,503359176
15 years (step)	0,002049955	0,00178993	0,00193033	0,493734124	0,464285042	0,476232223
Entire period (10 trials)	0,001920416	0,00174940	0,00183823	0,506087828	0,456749898	0,485982698

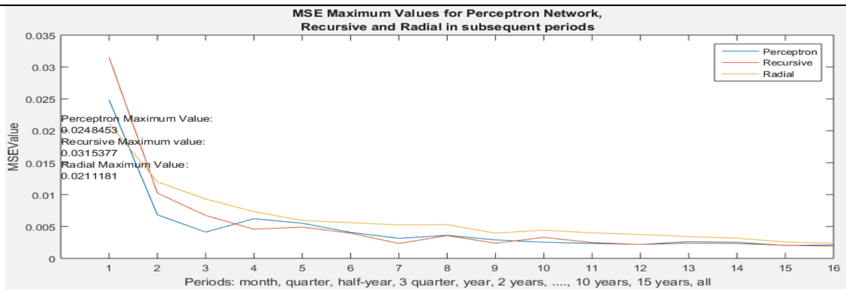
Based on the results obtained in Table 4, it can be seen that for the Recursive ANN, the fluctuations of both MSE and R2 are not as evident for shorter ranges as in the case of Perceptron ANN, however, a certain trend is also maintained, but in the case of longer ranges temporal values of the above-mentioned indicators are also more stable, i.e. in terms of having a smaller difference between the maximum, minimum and average values.

Table 5. Modeling results for the MSE error value obtained for Radial ANN. Source: Own study in the environment of MATLAB and Simulink [1].

The length of the quotation period on the PPE DAM	The obtained MSE values for the appropriate length of modeling periods			The obtained R2 values for the appropriate length of modeling periods		
	max	min	mean	max	min	mean
month	0,021118	7,65E-05	0,001832	0,91119	0,265607	0,677855
quarter	0,01202	0,000176	0,002065	0,756008	0,323661	0,577213
half a year	0,009293	0,000449	0,002154	0,685251	0,359375	0,521754
3 quarters	0,007324	0,00048	0,002205	0,617464	0,370122	0,487012
year	0,005938	0,000545	0,002245	0,579066	0,311879	0,461631
2 years	0,005597	0,000576	0,002248	0,53492	0,327358	0,421819
3 years	0,005242	0,000824	0,002064	0,485063	0,300481	0,401016
Four years	0,005289	0,000764	0,002276	0,457917	0,308585	0,382558
5 years	0,003955	0,000731	0,002089	0,438509	0,309328	0,382902
6 years (step)	0,004419	0,000918	0,002213	0,407743	0,299821	0,339848
7 years (step)	0,004006	0,001123	0,002173	0,354425	0,292831	0,328577
8 years (step)	0,003745	0,001074	0,002136	0,345692	0,284936	0,321588
9 years (step)	0,003422	0,001104	0,002122	0,345818	0,282638	0,316313
10 years (step)	0,003164	0,001171	0,002141	0,337234	0,276483	0,31149
15 years (step)	0,00256	0,00213	0,002367	0,288824	0,26906	0,279242
Entire period (10 trials)	0,002386	0,002386	0,002386	0,282168	0,282168	0,282168

The learning characteristics of the Radial ANN also do not differ from the previous two, the fluctuations of both MSE and R^2 for shorter intervals are greater, and the stability is greater for longer time intervals. In order to be able to compare the appropriate values obtained in particular periods of time, they are summarized in tables, respectively in Table 6 - for the MSE error and in Table 7 - for the determination index R^2.

Table 6. Selected graphs concerning MSE values for the periods listed in Table 3, 4 and Table 5. Markings: blue - Perceptron ANN, red - Recursive ANN, yellow - Radial ANN. Source: Own study in the environment of MATLAB and Simulink [1].

The length of the quotation period on the PPE DAM	MSE error waveforms
Course of **maximum MSE errors** for subsequent periods from one month, through quarter, half-year, year, 2 years, up to the entire period of PPE	

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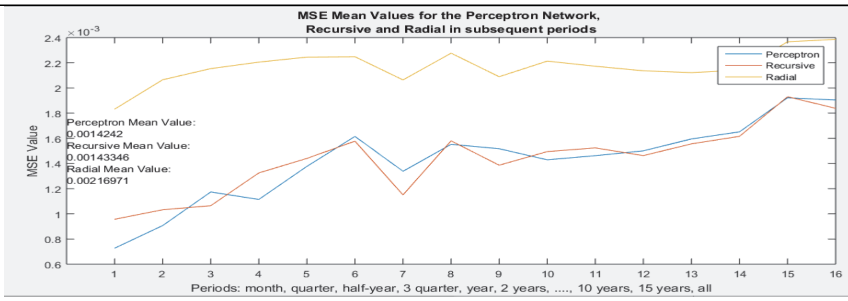
<tr><td>Course of average MSE errors for subsequent periods from one month, through quarter, half-year, year, 2 years, up to the entire period of PPE</td><td>
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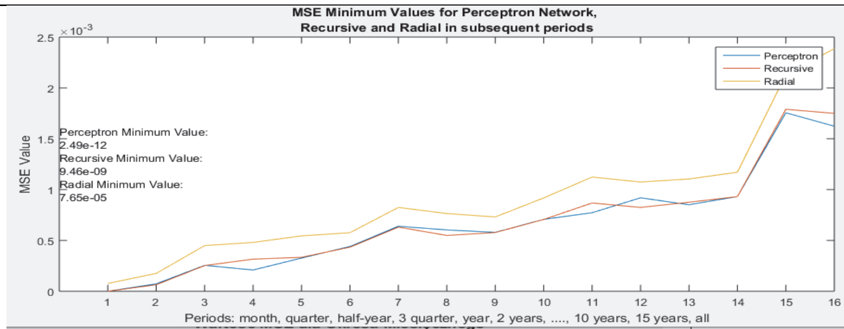
<tr><td>Course of minimum MSE errors for subsequent periods from one month, through quarter, half-year, year, 2 years, up to the entire period of PPE</td><td>
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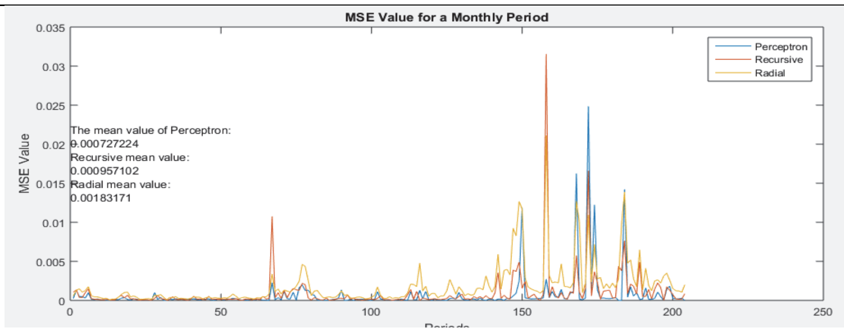
<tr><td>Course of MSE errors for monthly periods, taking into account the successive number of periods</td><td>
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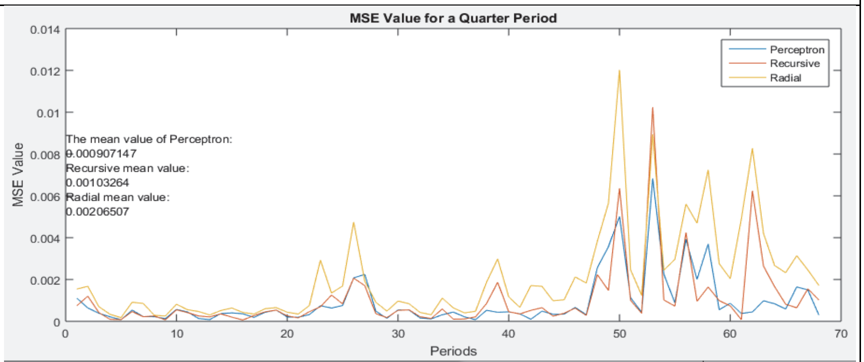
<tr><td>Course of MSE errors for quarterly periods with the successive number of periods</td><td>
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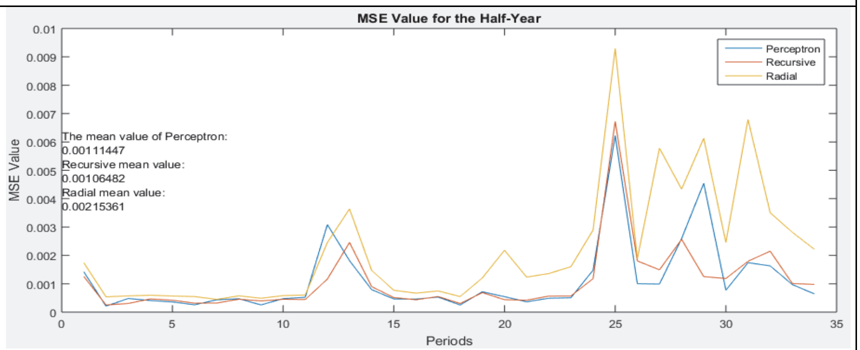
<tr><td>Course of MSE errors for half year periods with the successive number of periods</td><td>
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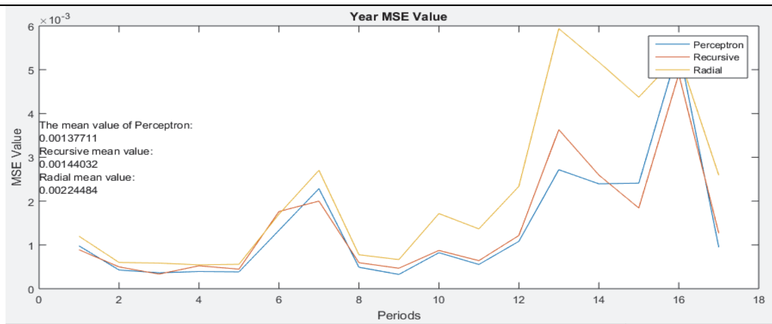
<tr><td>Course of MSE errors for qyear periods with the successive number of periods</td><td>
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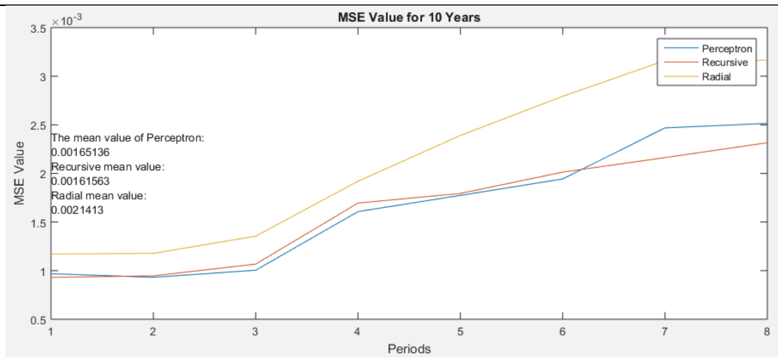
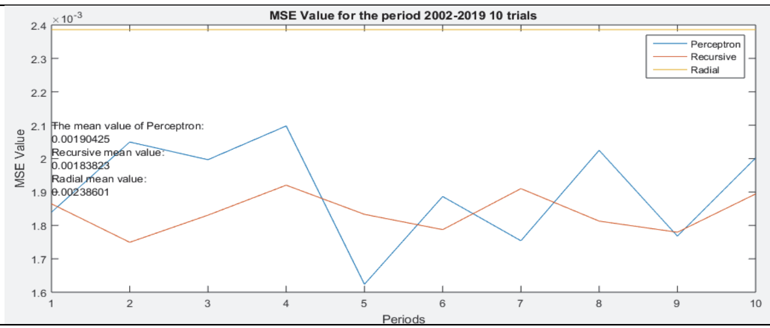
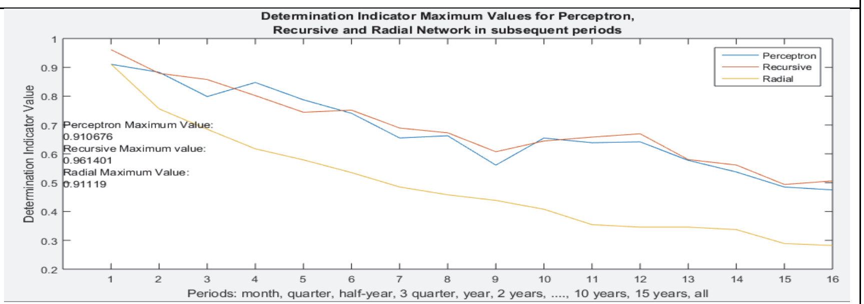
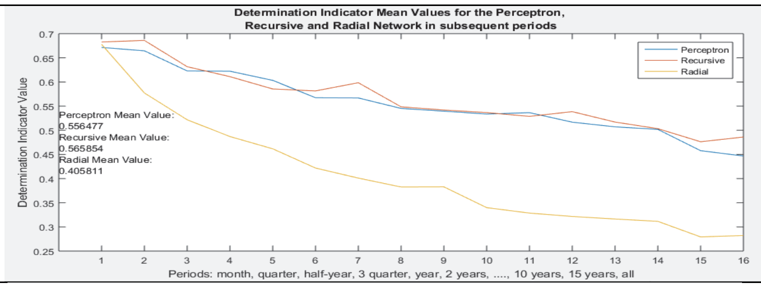
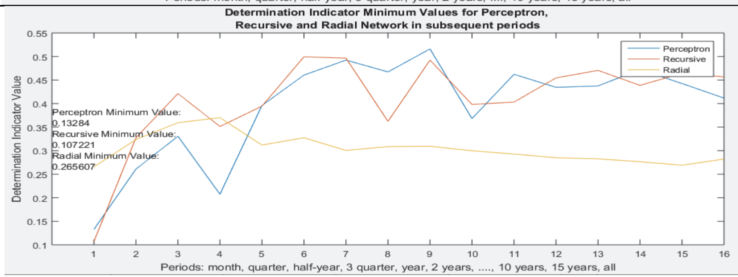
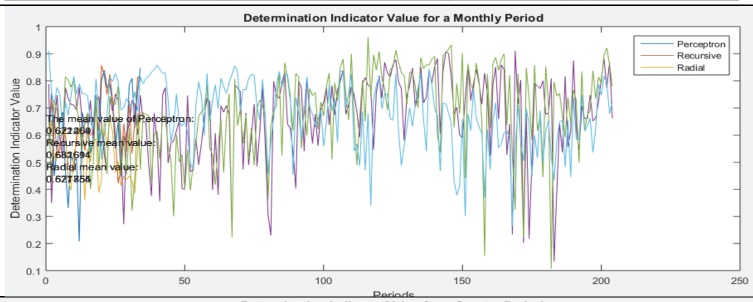
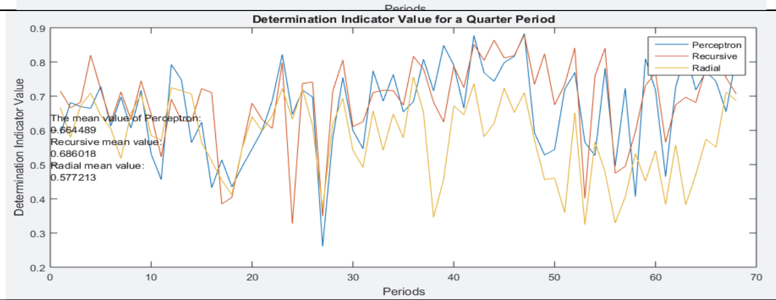
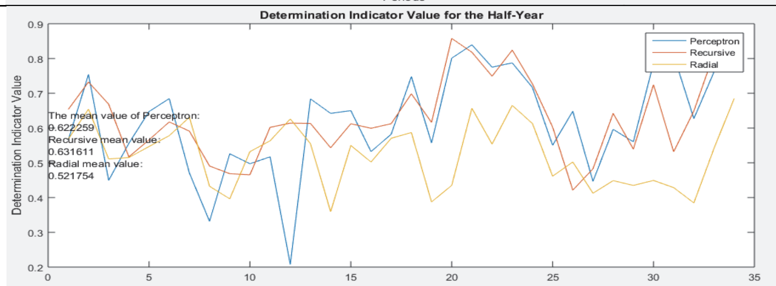
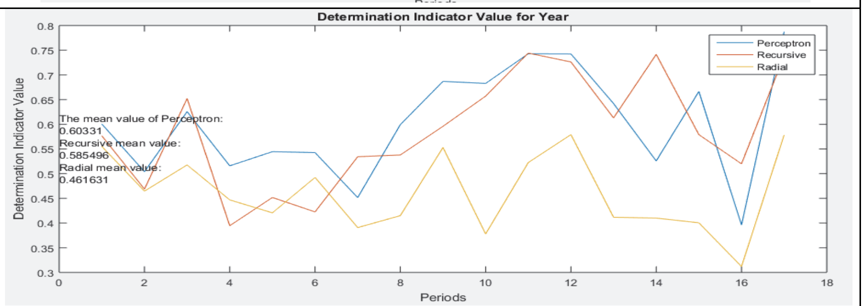
<tr><td>Course of MSE errors for 10 years periods with the successive number of periods</td><td>
</td></tr>
<tr><td>Course of MSE errors for the entire period of PPE DAM operation with 10 data attempts</td><td>
</td></tr>
</table>

Based on graphs shown in table 6 it can be stated that the MSE error curves for individual periods for Perceptron ANN and Recursive ANN are similar, but the Radial ANN, in principle in each obtained interval, has larger values of the MSE error, so it can be said that it is less useful in this sense for obtaining the neural model of the PPE DAM.

Table 7. Selected graphs concerning the R^2 values for the periods specified in Table 3, 4 and Table 5. Markings: blue - Perceptron ANN, red - Recursive ANN, yellow - Radial ANN. Source: Own study in the environment of MATLAB and Simulink Environment [1].

<table>
<tr><th>The length of the quotation period on the PPE DAM</th><th>Determination Indicator error waveforms</th></tr>
<tr><td>Course of maximum R^2 errors for subsequent periods from one month, through quarter, half-year, year, 2 years, up to the entire period of PPE</td><td>
</td></tr>
</table>

<table>
<tr><td>Course of average R^2 errors for subsequent periods from one month, through quarter, half-year, year, 2 years, up to the entire period of PPE</td><td>
</td></tr>
<tr><td>Course of minimum R^2 errors for subsequent periods from one month, through quarter, half-year, year, 2 years, up to the entire period of PPE</td><td>
</td></tr>
<tr><td>Course of R^2 errors for monthly periods, taking into account the successive number of periods</td><td>
</td></tr>
<tr><td>Course of R^2 errors for quarterly periods with the successive number of periods</td><td>
</td></tr>
<tr><td>Course of R^2 errors for half year periods with the successive number of periods</td><td>
</td></tr>
<tr><td>Course of R^2 errors for one year periods with the successive number of periods</td><td>
</td></tr>
</table>

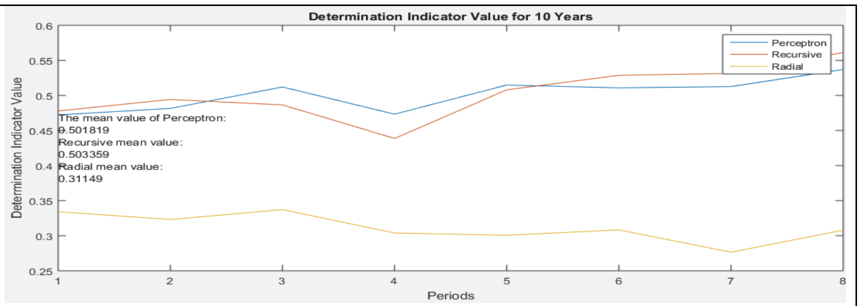
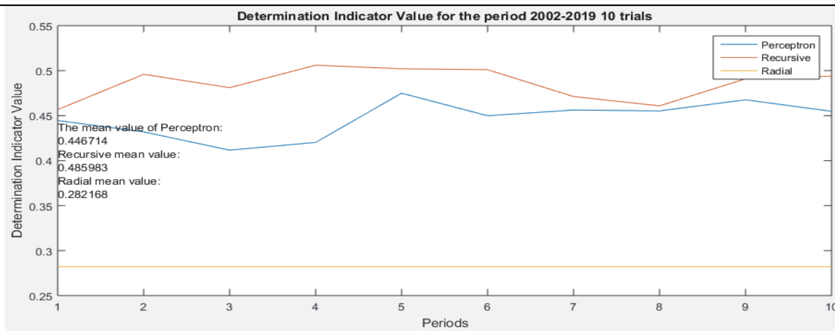
Course of R^2 errors for **10 years periods** with the successive number of periods	
Course of R^2 errors for the **entire period** of PPE DAM operation with 10 data attempts	

Table 7 shows the chart of the R^2 determination coefficient for various periods of the PPE's Day-Ahead Market operation, while, similarly to MSE (Table. 6), they are similar for Perceptron ANN and Recursive ANN, and Radial ANN. For Radial ANN in each examined case determination index R^2 is smaller, so it can be said that it was a weaker for learning the DAM neural model than the other two ANNs.

7. Conclusions and directions for further research

The results of the neural modeling of the Day-Ahead Market of the Polish Power Exchange were obtained, using numerical data relating to set time intervals from one month, through a quarter and a half-year period, to annual and multi-year periods and the entire period of its operation.

Market neural modeling was carried out on the basis of three models of artificial neural networks, ie: Perceptron Artificial Neural Network (the so-called Multi Layer Perceptron), ie Perceptron ANN, Recursive ANN and Radial ANN. As a result of neural modeling, 1,191 DAM models were obtained, which were assessed according to the criterion of the least error MSE and according to the determination index R^2.

It turned out that the Perceptron Artificial Neural Network is the best neural model of the Day-Ahead Market that can be used in prognostic studies, and the best neural modeling ranges taking into consideration value and variability were time intervals close to half of the year for Perceptron ANNs where the MSE error ranged from 0,006723 to 0,001065 and also slightly lesser for the same time intervals from 0,006723 to 0,00025243 for the Recursive ANN, which predisposes the adoption of the Perceptron ANN for the neural modeling of the DAM.

It is also turned out that the value of data set is important. The greatest fluctuations for both MSE and R^2 are characteristic of shorter ranges of subsets were the value are better.

It can be seen that the quality of the model is determined by the lowest possible MSE error and the highest possible value of the R^2 determination coefficient. Therefore, when selecting the size of the training set, both the size of the indicators (MSE, R^2) and their stability should be taken into account.

The test results will be helpful in building the improved DAM model because they provide an important indication of what type of neural network can be used to build such a model, as well as what data set is sufficient to properly build the model. This, of course, is only one aspect of choosing the right tools. Another for example is the selection of parameters of the network itself, e.g. the number of learning layers, activation functions, learning algorithm, etc. these aspects will be the subject of future research by the author. Many doubts are also raised by the model itself, which is based only on the volume and price as aggregating factors, such as: weather condition, technical aspects, market, political, etc. On the one hand, there are some attempts to analyze at least some of these factors [9], on the other hand, their selection is a serious challenge. This issue will also be the subject of research at the next stage.

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