

**Radosław MARŁĘGA<sup>1</sup>**

ORCID: 0000-0003-0174-5074

<sup>1</sup> PhD Student at Computer Science Institute  
Siedlce University of Natural Sciences and Humanities  
Faculty of Exact and Natural Sciences  
Institute of Computer Science  
ul. 3 Maja 54, 08-110 Siedlce, Poland

## **Correction of the parametric model of the Day-Ahead Market system using the Artificial Neural Network**

DOI: 10.34739/si.2022.26.06

**Abstract.** The paper shows that it is possible to correct the identification model of the Day-Ahead Market system by employing the Perceptron Artificial Neural Network. First, a simulation model of the DAM system at the POLPX has been built, and then it has been shown how the model can be corrected so that the weighted average electricity prices obtained are close enough to the exchange-quoted ones. Next, simulation, comparative and sensitivity studies of the model were carried out for forecast data for four characteristic hours: 6, 12, 18, and 24 of the following year. Many interesting research results were obtained, including a result of sensitivity testing it was shown that the obtained models can be used in forecasting studies.

**Keywords.** Artificial Neural Network, Day-Ahead Market, Modeling, Simulation, Comparative Research, Model Sensitivity Testing

## 1. Introduction

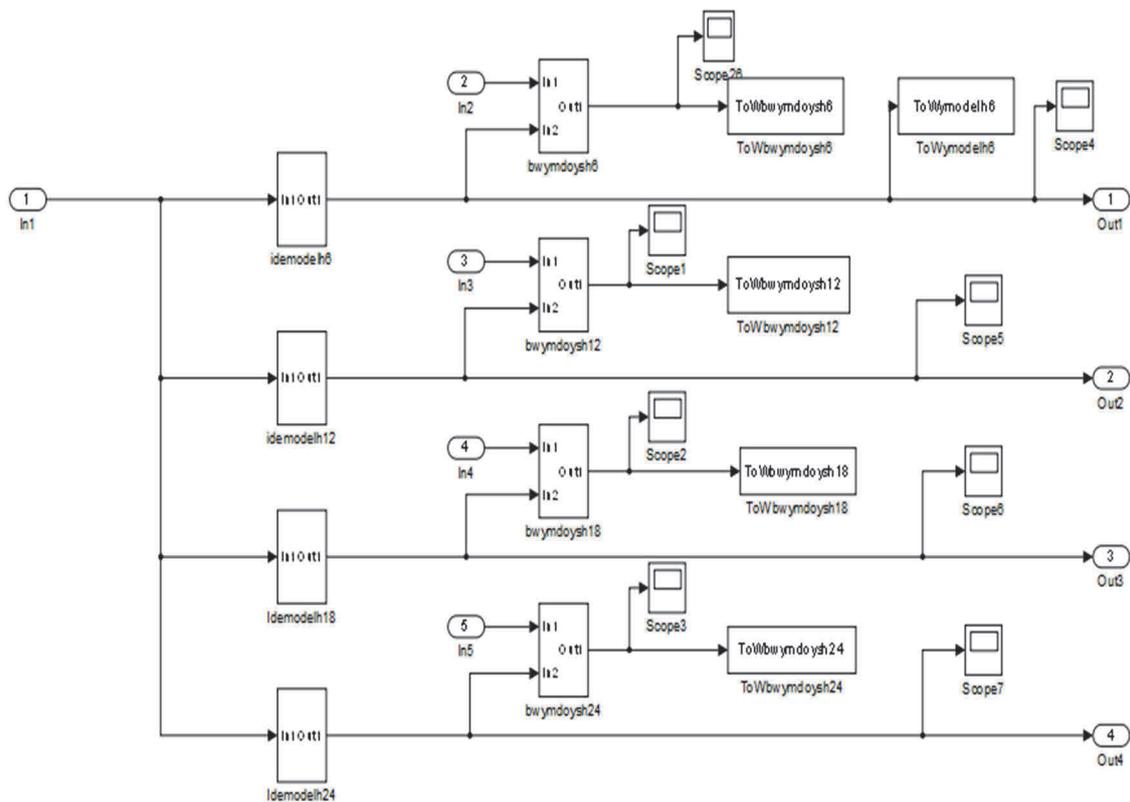
The conducted research concerns the modeling of the Day-Ahead Market (DAM) system functioning next to the Intraday Market at the Polish Power Exchange. [15, 33]. The DAM system models have been obtained as a result of identification research in terms of control and systems theory [15, 17, 23-25], and the obtained results have been published, among others, in numerous author's and co-author's papers [11-12, 27-29].

Ongoing research is concerned with obtaining system models through identification, nevertheless, various other attempts are also made to model systems, such as using the ARIMA method [3], GARCH [31], or using artificial neural network [4, 6-7, 10, 21], and even using fuzzy sets [13]. Interesting work in this regard is the work of price forecasting in a deregulated market [1], or the work [18] on forecasting based on a trend model and even using a crawling trend in forecasting studies [19].

It is worth mentioning that there are also comparative works showing different aspects of price modeling and forecasting such as the work [9] on a comparative study of intelligent methods concerning management systems, or a comparative study of artificial intelligence methods used in diagnostic methods [14]. A comprehensive work containing the results of research on price forecasting with different methods is the work [32] on the Day-Ahead Market system. There are also other methodologies for obtaining models of systems or processes, such as time series methods [2], which were not used in the research conducted in this study.

## 2. Day-Ahead Market System Model as an hourly model

The system studied was an hourly system related to the quotation at each hour of the day of electricity delivered and sold. Finally, the hourly simulation model was built in Simulink in the form of a block diagram, consisting of 24 essential Subsystems concerning identification models corrected with Artificial Neural Network (ANN) (Fig. 1).

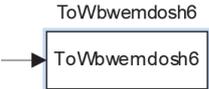
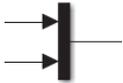


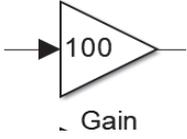
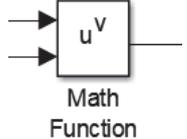
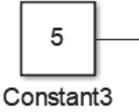
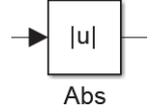
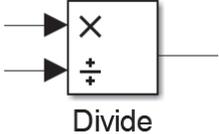
**Figure 1.** Hourly model of the DAM system. Symbols in Tab. 1 Source: own elaboration using Simulink [5].

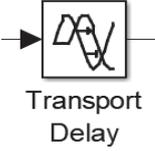
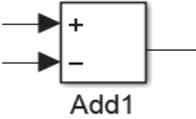
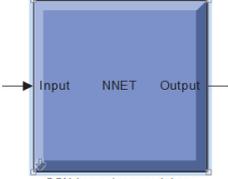
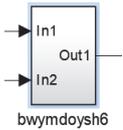
The model shown in Fig. 1 has been used within the framework of the present research as the identification-neural model of the Day-Ahead Market (DAM) system of the Polish Power Exchange for four hours, which is characteristic for Poland, that is for the hour 6, 12, 18 and 24. By way of identification, the MISO-type DAM system models for all 24 hours were obtained, and the models for four hours accepted in Poland as characteristic hours were selected for interpretation in this publication, and further studies can be used to compare the neighboring models for the above-mentioned characteristic hours in order to establish the observed trends. Comparative tests can also be performed to establish the number of characteristic hours over the period under consideration.

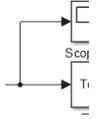
During its construction, in addition to the Subsystems determining the system models, the following Simulink blocks were used, among others: In, Subsystem determining the relative error of the model to the system, Scope, ToWorkspace, Out, etc., whose schemes and interpretation are shown in Tab. 1 [5].

**Table 1.** Summary of selected blocks of the DAM system model used in the parametric arx model corrected with ANN. Source: own elaboration using MATLAB and Simulink environment [5].

Function type	Description of the functions
	<p><b>From Workspace</b> – block that reads data values specified in time-series, matrices, or other forms from the MATLAB workspace, model workspace, or other workspaces. For matrix formats, each row of the matrix has a timestamp in the first column and a vector containing the corresponding data sample in the next column(s). For structure formats, we use the following notation: <code>var.time = [TimeValues]</code> <code>var.signals.values = [DataValues]</code> <code>var.signals.dimensions = [DimValues]</code>, e.g. <code>[tpp365 u242019]</code>, where: <code>tpp365</code> – vector controlling the data download, <code>u242019</code> – matrix of input values for data on the volume of sold ee in particular hours of the day in 2019.</p>
	<p><b>To Workspace</b> – inputs the signal and writes the signal data to the MATLAB workspace. During simulation, the block writes the data to an internal buffer. When the simulation ends or pauses, the data is written to the workspace. The data is not available until the simulation is stopped or paused. Block description e.g. <code>ToWbwemdosh6</code> – the name of the output data passed to the MATLAB workspace, in this case concerning the relative error between the model and the DAM system for hour 6 in 2019.</p>
	<p><b>Demux</b> – extracts the components of the input vector signal and outputs separate signals. The ports of the output signal are ordered from top to bottom. In the example under consideration, the input signal to the block is a matrix containing 24 quantities relating to the input signal <code>u</code>, that is, the volume of electricity supplied and sold, and the output signals are individual volumes of electricity for each hour of the day.</p>
	<p><b>Mux</b> – a block that combines multiple scalar inputs into a single vector output, where the input signal can be a vector signal. All input signals must be of the same data type. The elements of the output vector signal take the order from top to bottom or from left to right. In the example under consideration, this block was used to combine the model solidification signal with the DAM system solidification signal for 6 o'clock 2019 to obtain a waveform of both signals on a single graph.</p>

	<p><b>Gain</b> – in the case under consideration, the block is used as a proportional member, i.e., describing numerical values occurring in the model (e.g., data used to scale the input signal according to the value that is its parameter), here a constant value of 100: the fixed value of 100. The input signal and the block parameter (gain) can be a scalar, vector, or matrix. The user specifies the gain value as the value of the Gain parameter. The Gain parameter allows you to specify the degree of amplification or attenuation of the signal. The input and gain are then multiplied and the result is converted to the output data type using the specified rounding modes.</p>
	<p><b>Math Function</b> – a block of mathematical functions that performs typical mathematical functions, such as <math>e^x</math>, assigned by parameters. In the considered case, this block was used in the equalizer of the output signal from the neural model as a mathematical function of raising to a power at the given parameter <math>v</math> (<math>u^v</math>).</p>
	<p><b>Product</b> – a function block of multiplication and division of scalar and non-scalar signals of the same dimensions or matrix multiplication and inversion. In the model considered in the publication, this block is used to determine the model solidification and the system solidification (in the example presented, the model solidification is determined for 12 o'clock 2019).</p>
	<p><b>Constant</b> – a block that generates a real or complex constant value. The output can be a scalar, vector, or array signal. The output signal from the block has the same dimensions and elements as the input signals to the block, in the case under consideration these were constant values.</p>
	<p><b>Abs</b> – a block to generate the absolute value of the output. In the cases modeled in the publication, the block was used to obtain the absolute value of the discrepancy between the two signals, the parametric-neural signal and the actual signal for 6 o'clock 2019.</p>
	<p><b>Divide</b> – a block that divides the value of the signal entered into the numerator (designation: <math>x</math>) by the value of the signal entered into the denominator (designation: <math>\div</math>). The output signal from the block is the signal resulting from the division as an object of numeric type T, where the numerator and denominator must have the same dimensions. In the case under consideration, this block was used to determine the efficiency of the DAM system.</p>

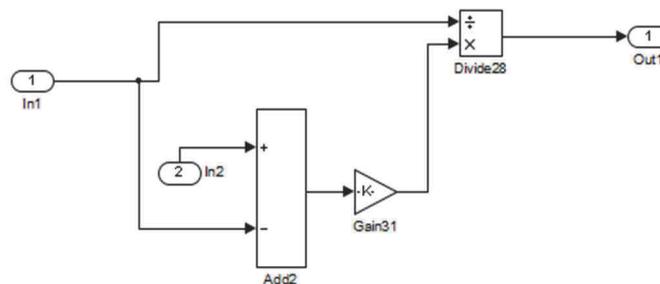
 <p>Transport Delay</p>	<p><b>Transport Delay</b> – a block that delays the input to the block by a specified unit of time, e.g., by one unit of delay resulting from the time delay operator <math>z^{-i}</math> (e.g., for <math>i=1</math>) found in the parametric model arx. At the beginning of the simulation, the block outputs the initial output parameter until the simulation time exceeds the time delay parameter <math>z^{-i}</math>, after which the input delay is generated. For discrete signals, the output occurs at the required time with the corresponding value. In the models considered in this paper, this block was used in the idpoly model as a parametric-neural model of the TGE S.A. DAM system.</p>
 <p>Skuteczność modelu6</p>	<p><b>Scope</b> – a block displaying signal waveforms generated during the simulation. In the case under consideration, the signal displayed is the effectiveness of the DAM system model for hour 6 in 2019.</p>
 <p>Add1</p>	<p><b>Sum</b> – a block that allows performing addition and/or subtraction operations on signals entering the block. The number and type of inputs are parameters of the block, as well as the type of shape of the block. In the case considered, the block was used to determine the absolute error between the system efficiency and the model efficiency.</p>
 <p>idpoly(arx6101h62019) Idmodelarx1h6</p>	<p><b>Idpoly</b> – a block implementing a function of the form idpoly, in the case considered in the publication idpoly(arx6101h62019), which is an implementation of the parametric discrete model arx6101h62019 in Simulink. The function requires its argument as an object of type idpoly(DAM system model) to be stored in Workspace, as in the considered case for hour 6 2019. This function is implemented in Simulink using a block that supports in general models also with continuous time or without input-output delays. The initial states must be a vector of length equal to the model row. For the idpoly model under consideration, the initial conditions are zero.</p>
 <p>SSN korygująca model arx</p>	<p><b>NNET</b> – a block simulating the operation of an Artificial Neural Network taught to correct the output signal from a parametric discrete arx model. In the example considered, the model is arx6101h62019, that is, the model of the DAM system for hour 6 2019. This block assumes the parameters of an ANN designed and implemented using NNT.</p>
 <p>bwymdoysh6</p>	<p><b>Subsystem</b> – a block in the example considered in the publication is designated Bwymdoysh6 and is a Subsystem containing a model for determining the absolute error and relative error between the parametric-neural model and the DAM system for hour 6 2019.</p>
 <p>In1</p>	<p><b>Inport</b> – input link block to the Subsystem from the system environment (usually from a host system). These links are automatically numbered in order from the highest level starting with input 1.</p>

	<p><b>Output</b> – output link block from the Subsystem to the system environment (usually to a host system). They are automatically numbered in order from the highest level starting from input 1. You can assign a port a sampling time as the rate of sending the signal from the system to the environment.</p>
	<p><b>Coupling link</b> – a method of connection that separates an incoming scalar or vector signal into two identical signals (called an abutment).</p>

The obtained signals from the identification models were corrected using ANN which reduced the model to a hybrid identification-neural model [10, 13, 20, 26-28, 30]. The subsystem concerning the DAM system model along with the model correction using Artificial Neural Network was built with the following blocks: In, Idmodel, Gain, Custom Neural Network, Scope, ToWorkspace, and Out and shown in Fig. 2, with the basic block of this model being the Idmodel type blocks, such as the Idmodel block for hour 6 of 2019 in the form:

$$yidmodelh62019=idpoly(arx6101h62019), \quad (1)$$

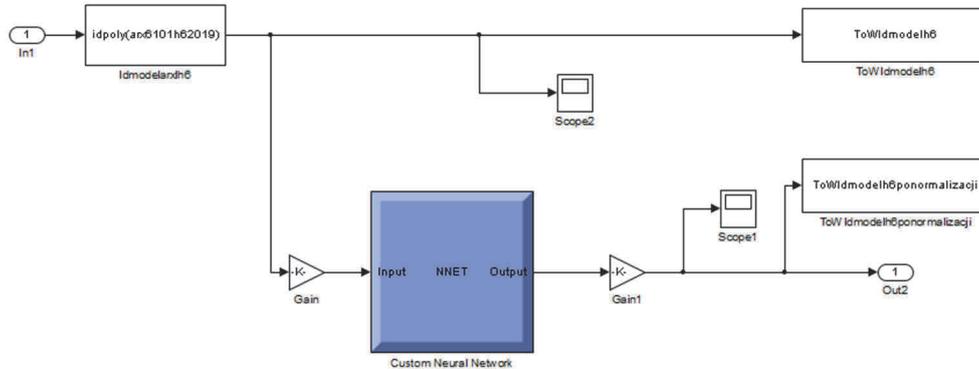
whose argument is a parametric model with an input containing 24 input quantities about the volume of delivered and sold ee at each hour of the day, in the considered example for hour 6 in 2019.



**Figure 2.** Subsystem determining the relative error of the model to the system. Designations in Tab. 1. Source: own elaboration using Simulink [5].

The simulation studies with the use of the parametric-neural model have shown, among others, that the identification has resulted in similar output values from the parametric-neural model of the DAM system concerning the output values from the DAM system, determined employing the model relative error to the system shown in the Subsystem as in Fig. 2, that is based on the volume-weighted average ee price in the considered case for the sixth hour (h6) of 2019. Further, an attempt has been made to correct the obtained test results using Perceptron

ANN (Fig. 3), which has been taught to correct the signal, which is the volume-weighted average ee price in the studied four hours of the day (6, 12, 18 and 24) for the year 2019.



**Figure 3.** Subsystem determining the DAM system model. Symbols in Tab. 1 Source: own elaboration using Simulink [5].

The determined relative errors for each of the four hours for 2019 for the ANN-corrected DAM system identification model ranged from a value of 5.3898% to a value of 10.5419%. The obtained annual results, as well as the results for a randomly selected month (December 2019) and a randomly selected week, including the exclusion for weekdays (the first full week of December), are provided in Tab. 2.

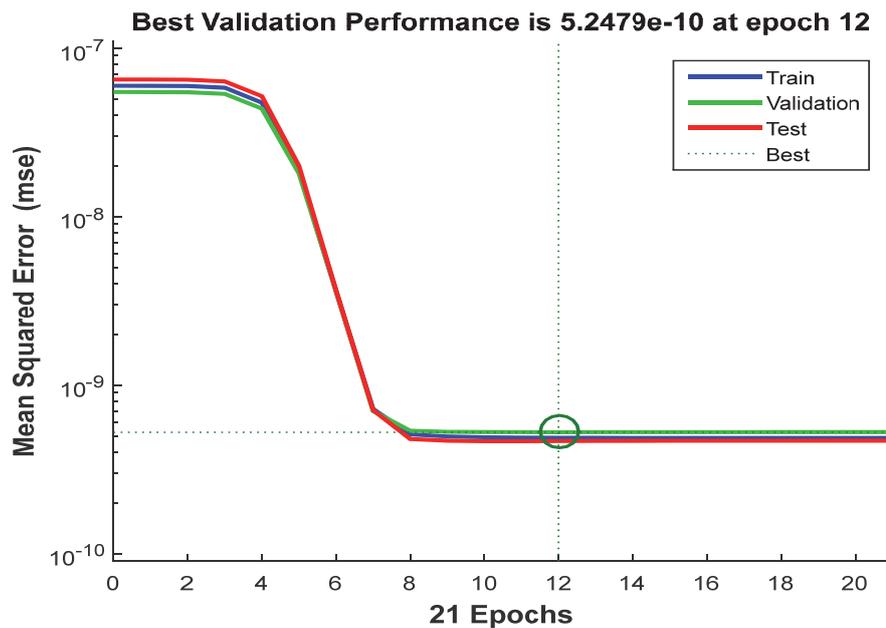
**Table 2.** Summary of relative errors [%] for selected periods of 2019 (year, month of December, week two). Source: own elaboration using MATLAB and Simulink [5].

Specification	2019	Selected months	Selected months (working days only)	Selected weeks	Selected weeks (working days only)
Idmodel h6	5.46	4.86	4.816	3.016	2.856
Idmodel h6 with ANN correction	<b>5.39</b>	3.46	2.52	0.71	1.26
Idmodel h12	11.29	13.69	13.92	11.55	11.43
Idmodel h12 with ANN correction	<b>10.54</b>	18.45	20.63	20.85	23.20
Idmodel h18	11.77	12.40	12.44	14.91	18.85
Idmodel h18 with ANN correction	<b>9.68</b>	8.24	7.04	9.61	10.27
Idmodel h24	6.18	11.02	11.70	11.61	12.10
Idmodel h24 with ANN correction	<b>6.39</b>	11.15	10.83	8.99	10.18

### 3. Perceptron ANN as a corrector of the output quantities of the DAM system model

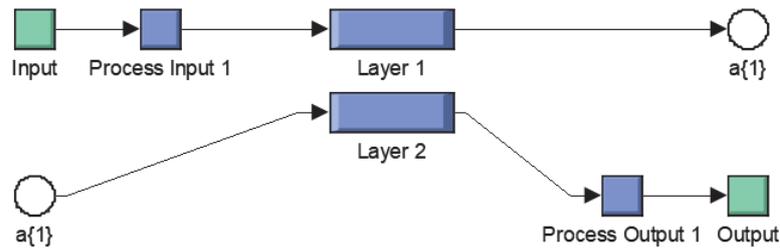
The perceptron ANN was obtained as a result of learning the Artificial Neural Network on the normalized quantities concerning the volume-weighted average ee price in a given hour of

the day (6, 12, 18, and 24) obtained as an output signal from the Idmodel sub-system (treated as an input to the ANN) and the volume-weighted average ee price in a given hour of the day quoted on the DAM (treated as an output from the ANN). The mean square error MSE obtained as a result of learning the ANN has been presented in Fig. 4, which for epoch zero amounted to  $1.70 \cdot 10^{-7}$ , and after a sharp decrease, it reached a stabilized value already in epoch 9 amounting to  $9.79 \cdot 10^{-13}$  (no overfitting phenomenon occurred).

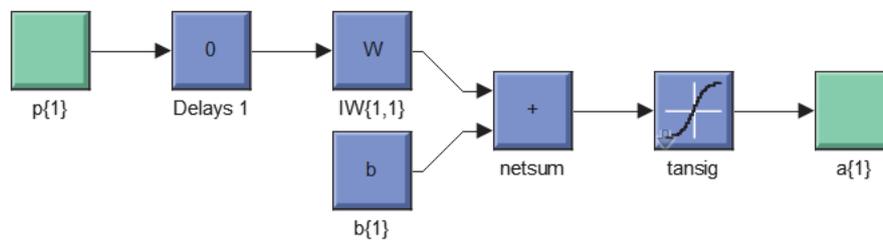


**Figure 4.** MSE mean squared error of learning ANN neural model of DAM system as signal equalizer from Idmodel parametric model. Symbols: Train – learning error, Validation – validation error, Test – testing error, Best – fitting the neural model to real data in the fifth epoch, Epochs – ANN learning epochs. Source: own elaboration using Neural Network Toolbox [5].

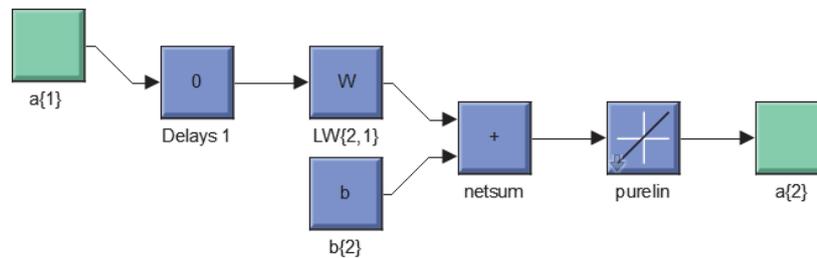
The obtained ANN Subsystem consists of two layers of neurons shown as ANN block subsystems in Fig. 5, with the content for layer one with tansig() neuron activation function shown in Fig. 6 and for layer two with purelin() neuron activation function shown in Fig. 7 [5].



**Figure 5.** ANN architecture of the learned neural output equalizer model from Idmodel for hour 6 2019. Labels: Layer 1 – Layer 1 ANN, that is, the hidden layer of neurons, Layer 2 – Layer 2 ANN, that is, the output layer of neurons, other designations refer to the inputs and outputs of each layer of neurons. Source: own elaboration using Neural Network Toolbox [5].

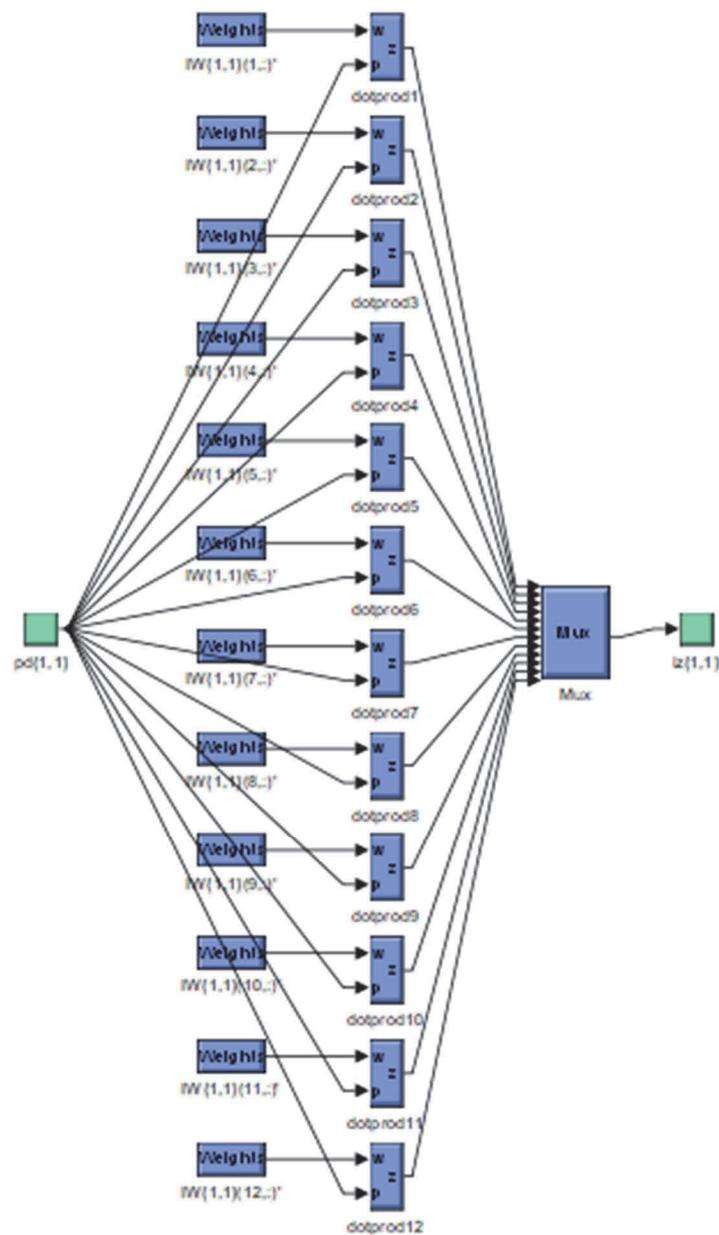


**Figure 6.** ANN architecture of layer one of the Idmodel neural output equalizer model for hour 6 2019. Denotations:  $IW\{1,1\}$  – weight matrix,  $b\{1\}$  – bias vector, tansig – neuron activation function block, other designations refer to inputs and outputs of individual neuron layers. Source: own elaboration using Neural Network Toolbox [5].

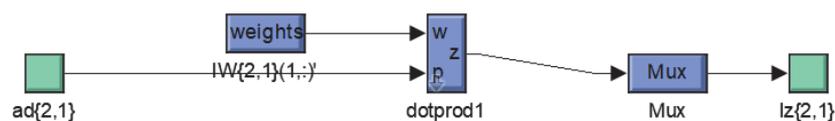


**Figure 7.** ANN architecture of layer two of the Idmodel neural output equalizer model for hour 6 2019. Denotations:  $LW\{2,1\}$  – weight matrix,  $b\{2\}$  – bias vector, purelin – neuron activation function block, other designations refer to inputs and outputs of individual neuron layers. Source: own elaboration using Neural Network Toolbox [5].

This model is a neural model built from a Perceptron ANN composed of two layers of neurons with unidirectional signal flow from input to output, with all neurons of the previous layer connected to all neurons of the next layer. Fig. 8 and Fig. 9 show the architecture of layer one neurons **W1** and layer two neurons **W2**, respectively [26].

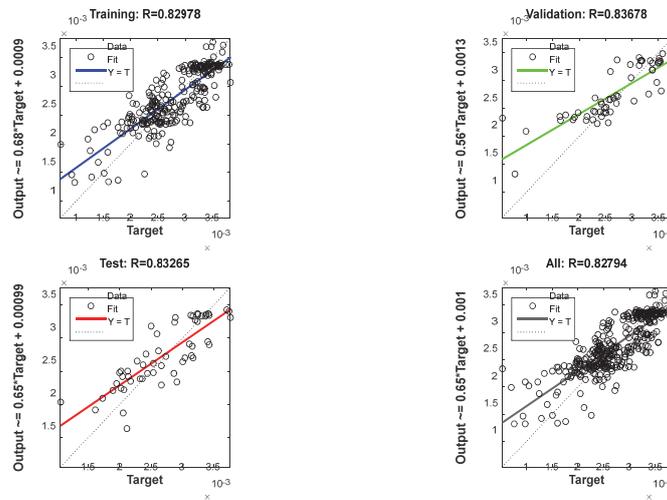


**Figure 8.** Layer one ANN architecture for the  $W_1$  weight matrix of the Idmodel neural output equalizer for hour 6 2019. Denotations:  $IW\{1,1\}(i,:)$  – the corresponding weights of the weight matrix  $W_1$ ,  $i=1-12$ . Other notations as in Tab. 1. Source: own development using Neural Network Toolbox [5].



**Figure 9.** Layer 2 ANN architecture for the  $W_2$  weight matrix of the Idmodel neural output equalizer for hour 6 2019. Denotations:  $IW\{2,1\}(1,:)$  – the weight of the  $W_2$  weight matrix. Other designations as in Tab. 1. Source: own development using Neural Network Toolbox [5].

Learning the ANN of the signal equalizer model output from Idmodel resulted in a regression index of  $R=0.82978$ , a relatively high index indicating a good fit of the equalizer (Fig. 10).



**Figure 10.** Regression index of the ANN learning process of the Idmodel neural output matching for hour 6 2019 to the real data of the DAM system. Symbols: Training – learning error, Validation – validation error, Test – testing error, All – fitting the neural model to real data, x-axis (Target) – learning target, y-axis (Output) – output. Source: own elaboration using Neural Network Toolbox [5].

The model after learning was then tested resulting in a regression index of  $R=0.83265$  and after undergoing validation it was obtained as  $R=0.83678$ .

The learning resulted in the following layer one weights and biases for hour 6 of 2019:

$$IW\{1,1\}(i,:) = [-13.9573; -13.9395; \dots; -14.0015; 14.0529], \quad (2)$$

$$\mathbf{B1} = [14.0409; 10.9558; \dots; -10.8863; 13.9459] \quad (3)$$

and thus the summators of the weighted inputs of the hidden layer neurons are as follows:

$$\begin{aligned} net_{11}^1 &= -13.9573 \cdot u_1 + 14.0409, \\ net_{12}^1 &= -13.9395 \cdot u_1 + 10.9558, \\ &\dots \\ net_{112}^1 &= 14.0529 \cdot u_1 + 13.9459. \end{aligned} \quad (4)$$

Similarly, the following weights and bias were obtained for the output layer:

$$IW\{2,1\}(1,:) = [0.30678 \ -0.12441 \ \dots \ -0.024817 \ 0.20338], \quad (5)$$

$$\mathbf{B2} = [0.025585], \quad (6)$$

hence the summation of the weighted inputs of the neurons of the second layer, that is, the output layer is as follows:

$$\begin{aligned} net_1^2 = net_{11}^2 + net_{21}^2 + \dots + net_{101}^2 = 0.30678 \cdot u_1 - 0.12441 \cdot u_2 + \dots \\ + 0.20338 \cdot u_{12} + 0.025585, \end{aligned} \quad (7)$$

where:

$net_{ij}^k$  – weighted input combiner between the  $i$ -th output and the  $j$ -th neuron of the  $k$ -th layer,

bias (**B1**, **B2**) – vectors of neuron weights with constant input value for layer 1 and layer 2 neurons, respectively,

$\mathbf{IW}\{1,1\}(i,:)$  – corresponding weights of the weight matrix **W1**,  $i=1-12$ ,

$\mathbf{IW}\{2,1\}(1,:)$  – weight of the weight matrix **W2**,  $i=1$ .

Considering for the first layer the neuronal activation function in the form of  $tansig()$  and for the second layer the function in the form of  $purelin()$ , the following is obtained:

$$tansig(net_{ij}^1) = \frac{2}{(1+\exp(-2 \cdot net_{ij}^1))^{-1}}, \quad (8)$$

and

$$purelin(net_{ij}^2) = a \cdot net_{ij}^2, \quad (9)$$

where:

$a$  – proportionality factor, which in the case under consideration was 1.

from here on it is obtained for the hidden layer:

$$\begin{aligned} y_1^1 = tansig(net_{11}^1) &= \frac{2}{(1+\exp(-2 \cdot (-13.9573 \cdot u_1 + 14.0409)))^{-1}}, \\ y_2^1 = tansig(net_{12}^1) &= \frac{2}{(1+\exp(-2 \cdot (-13.9395 \cdot u_1 + 10.9558)))^{-1}}, \\ &\dots \\ y_{12}^1 = tansig(net_{112}^1) &= \frac{2}{(1+\exp(-2 \cdot (14.0529 \cdot u_1 + 13.9459)))^{-1}}, \end{aligned} \quad (10)$$

and respectively for the output layer:

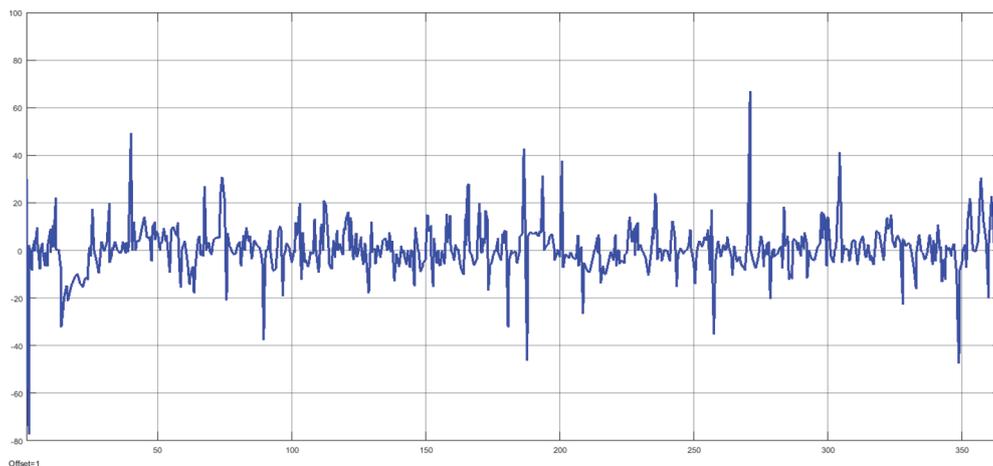
$$\begin{aligned} y_{SSN} = y_1^2 = purelin(net_1^2) = 0.30678 \cdot u_1^2 - 0.12441 \cdot u_2^2 + \dots \\ + 0.20338 \cdot u_{12}^2 + 0.025585. \end{aligned} \quad (11)$$

Thus, the neural model in the form of a Perceptron ANN learned to correct the identification model error consists of relations (6.10), (6.11), with the output of layer one being the input to layer two.

#### 4. Comparative study of the model in relation to the DAM system

The comparative tests of the model concerning the DAM system were carried out for each hour of the day, with the dissertation including the results of the tests for the four adopted p. 1, that is, for the contractual hours: 6, 12, 18 and 24.

A simulation model extended with comparative models structured as in Fig. 1-3 were used to compare the model against the system. In each case, the absolute error or discrepancy between the model output and the system output was first determined. The relative error curves for the above four hours are given in Fig. 11–12.

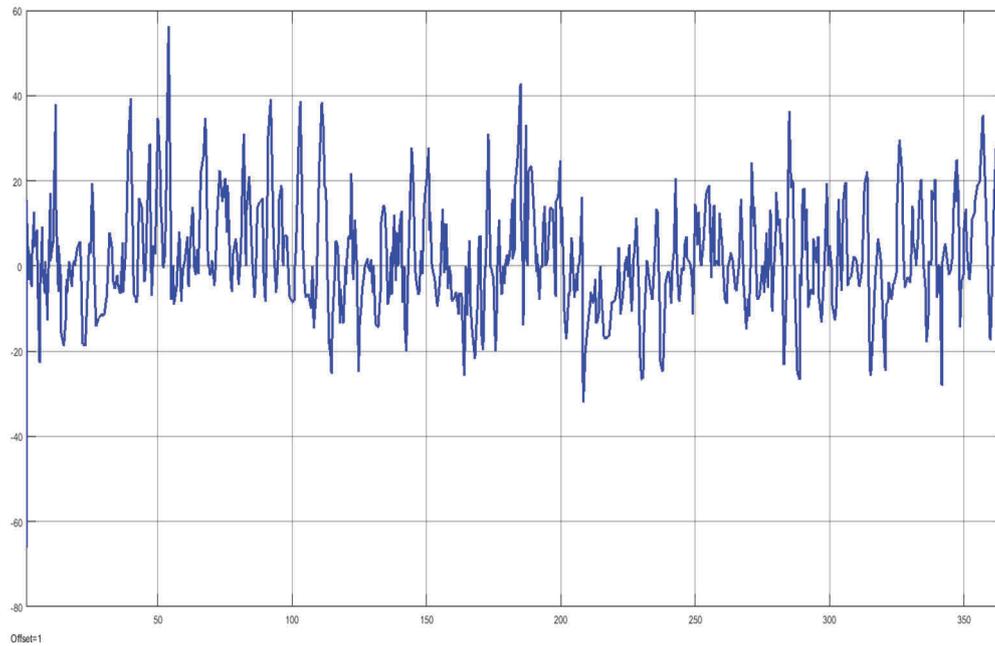


**Figure 11.** Relative error curves of the model versus the DAM system for hour 6 2019. Markings: X-axis - long time (year). Source: own elaboration using Simulink environment [5].

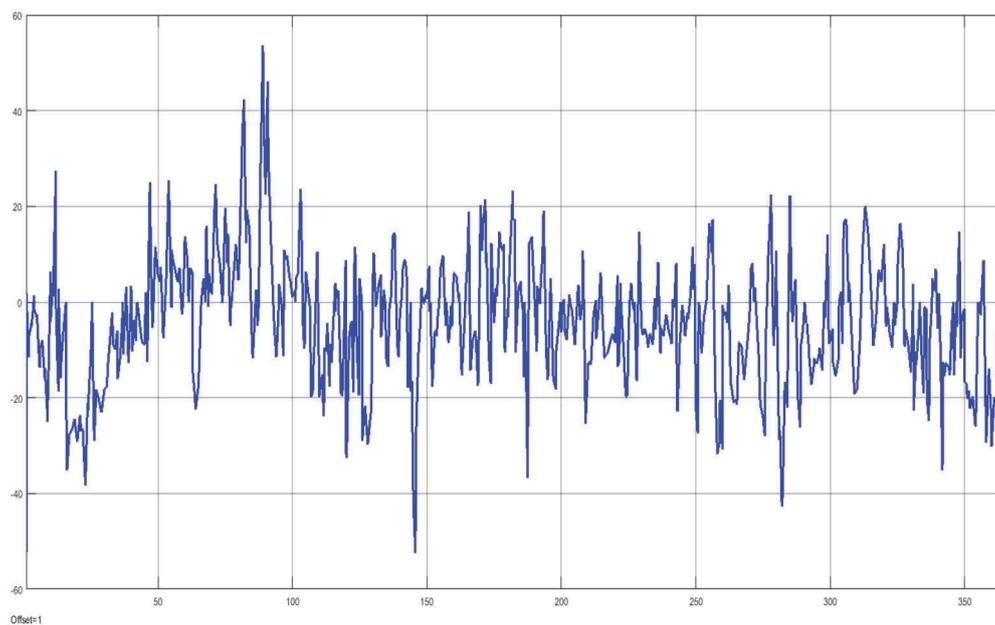
In addition, the MAPE errors of the DAM system model for hours 6, 12, 18, and 24 of the year 2019 and the DAM system model corrected with ANN were determined. The MAPE error for selected periods of FY 2019 is provided in Tab. 3. The FY 2019 MAPE errors ranged from 5.46% for hour 6 for the identification model to 11.85% for hour 18, and when corrected with ANN from 5.39% for hour 6 (0.07% decrease) to 9.92% for hour 18 (1.93% decrease in error).

Equally small MAPE errors were also obtained for selected weeks of the year, in the example considered for the second week in December 2019. The MAPE error ranged for this full week (7 days) from 3.01% for the 6 o'clock hour to 11.24% for the 12 o'clock hour, and for the working days of this week (5 days) from 2.85% for the 6 o'clock hour to 13.91% for the 12 o'clock hour.

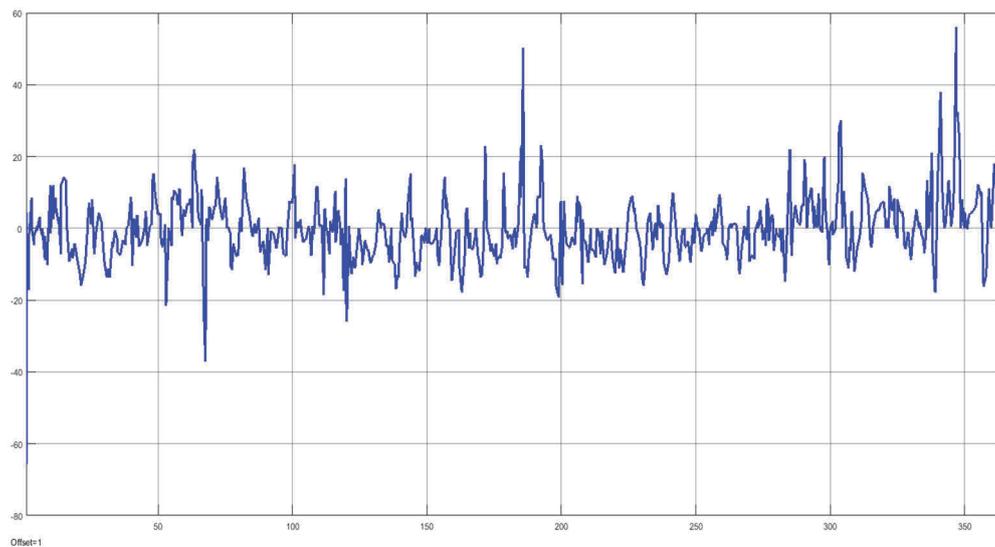
It is noted that among the four considered hours of the day of the year 2019, the MAPE error was always obtained as the smallest for the 6 o'clock hour and the largest for the 6 o'clock or 12 o'clock hour.



**Figure 12.** Relative error curves of the model versus the DAM system for hour 12 2019. Markings: X-axis – long time (year). Source: own elaboration using Simulink environment [5].



**Figure 13.** Relative error curves of the model versus the DAM system for hour 18 2019. Markings: X-axis – long time (year). Source: own elaboration using Simulink environment [5].



**Figure 14.** Relative error curves of the model versus the DAM system for hour 24 2019. Markings: x-axis – long time (year). Source: own elaboration using Simulink environment [5].

**Table 3.** Summary of MAPE errors [%] for selected periods of 2019 (year 2019, month December, week two). Source: own elaboration using MATLAB and Simulink [5].

Specification	Whole 2019 [%]	Selected months [%]	Selected months (working days only) [%]	Selected weeks [%]	Selected weeks (working days only) [%]
Idmodel h6	5.46	6.57	6.15	3.01	2.85
Idmodel h6 with ANN correction	5.39	6.81	6.51	3.77	4.58
Idmodel h12	11.50	13.07	14.33	11.24	13.91
Idmodel h12 with ANN correction	9.55	12.21	12.49	12.81	14.48
Idmodel h18	11.85	8.30	8.60	3.65	3.53
Idmodel h18 with ANN correction	9.92	11.86	11.99	5.98	5.77
Idmodel h24	6.94	7.89	7.93	8.80	8.89
Idmodel h24 with ANN correction	6.31	11.07	11.55	5.99	5.57

## 5. Results of sensitivity testing of the DAM system model

Sensitivity studies of the DAM system model were performed on the DAM system model for hour 6 of the year 2019 for the contractual figures for the year 2020. The behavior of the model was investigated with the input data on the volume of delivered and sold ee from the

year 2020, assuming that the first fifteen inputs are related to the initial conditions of the model (due to the lags present in both the  $A(z)$  and  $B(z)$  polynomials). The MAPE error was obtained and is summarized in Tab. 4 for the selected year 2020 periods.

**Table 4.** Summary of MAPE errors [%] for selected periods of 2020 (year 2020, month December, week two). Source: own elaboration using MATLAB and Simulink [5].

<b>For the hour 6</b>	<b>Whole 2020 [%]</b>	<b>Selected months [%]</b>	<b>Selected months (working days only) [%]</b>	<b>Selected weeks [%]</b>	<b>Selected weeks (working days only) [%]</b>
Idmodel	32.00	7.00	6.7	10.05	4.58
Idmodel with ANN correction	<b>31.33</b>	<b>7.24</b>	<b>5.99</b>	<b>6.96</b>	<b>3.83</b>

The best result in terms of the sensitivity of the 2019 model for the 2020 input was for working days in the second week of December 2020 (3.83%), which is comparable to published data, and the worst for the entire 2020 (31.33%), which is indeed relatively high, but the literature on the subject lacks research results for such long periods of time.

## 6. Conclusion and further research

Simulation studies with the use of the parametric-neural model have shown, among other things, that the identification has resulted in similar output volumes from the parametric-neural model of the DAM system concerning the output volumes from the DAM system, determined with the use of the model relative error to the system shown in the Subsystem as in Fig. 2, i.e. based on the volume-weighted average ee price in the considered case for the sixth hour (h6) of 2019.

Further, an attempt was made to correct the obtained test results using Perceptron ANN (Fig. 3), which was taught to correct the signal, which is the volume-weighted average price of electricity in the studied four hours of the day (6, 12, 18 and 24) for the year 2019. The determined relative errors for each of the four hours for the year 2019 for the identification model of the DAM system corrected using ANN ranged from the value of 5.3898% to the value of 10.5419%.

The annual results obtained, as well as the results for a randomly selected month (December 2019) and for a randomly selected week, including the exclusion for working days (the first full week of December), are provided in Tab. 2. The research continues, among other things, to investigate the effectiveness and efficiency, especially the robustness of the models and the

DAM system using the relationship between effectiveness and implementation efficiency noted in the work of [8], among others.

## References

1. Aggarwal S.K., Saini L.M., Kumar A.: Electricity price forecasting in deregulated markets: A review and evaluation, *International Journal of Electrical Power & Energy Systems*, No. 31, 2009, pp. 13-22.
2. Box G. E. P., Jenkins G. M.: *Analiza szeregów czasowych. Prognozowanie i sterowanie.* (Eng. Time series analysis. Forecasting and control), PWN, Warszawa, 1983, pages 574.
3. Conejo A. J., Plazas M. A. , [et all]: Day-ahead electricity price forecasting using the wavelet transform and ARIMA models. *IEEE Transaction on Power System*, No. 20(2), 2005, pp.1035–1042.
4. Ejdys J., Halicka K., Godlewska J.: Prognozowanie cen energii elektrycznej na giełdzie energii (Eng. Forecasting electricity prices on the power exchange). *Zeszyty Naukowe Politechniki Śląskiej, Seria: Organizacja i Zarządzanie, Zeszyt 77, Nr kol. 1927*, 2015, pp. 1-10.
5. Guide for MATLAB, Guide for Simulink, Guide for System Identification Toolbox, Guide for Control System Toolbox, Guide for Neural Network Toolbox. The MathWorks®. *Getting Started Guide*, 2021b.
6. Halicka K.: *Skuteczność prognozowania w zarządzaniu transakcjami na giełdzie energii* (Eng. Effectiveness of forecasting in managing transactions on the power exchange), rozprawa doktorska pod kierunkiem prof. dr hab. inż. Joanicjusza Nazarko, Wydział Zarządzania Uniwersytetu Warszawskiego, Warszawa, 2006, pages 207.
7. Jiang L.L., Hu G.: Day-Ahead Price Forecasting for Electricity Market using Long-Short Term Memory Recurent Neural Network. 2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV), Singapore, Nov. 19-21, IEEE Digital Library, 2018, pp. 949-954.
8. Kowal W.: *Skuteczność i efektywność – zróżnicowane aspekty interpretacji* (Eng. Effectiveness and efficiency - various aspects of interpretation), *Kwartalnik Naukowy pt. Organizacja i Kierowanie*. Nr 4 (157), SGH, Warszawa, 2014, pp. 12-23.
9. Labib N., Wadid E.: Comparative study of Intelligent Systems for Management of GIT

- Cancers, MATEC Web of Conferences 125, CSCC 2017, 2017, pp. 1-6.
10. Mandal P., Senyju T. [et all]: A Novel Approach to Forecast Electricity Price for PJM Using Neural Network and Similar Days Method, IEEE Transactions on Power Systems, 22(4), 2007, pp. 2058 – 2065.
  11. Marłęga R.: State-space model and implementation Polish Power Exchange in MATLAB and Simulink environments. Information Systems in Management. Vol. 6, No. 4, 2017, pp. 294-308.
  12. Marłęga R., Tchórzewski J.: Identification modeling of Polish electric power exchange, Information Systems in Management, No. 2, Vol. 5, 2016, pp. 195-204.
  13. Mandal P., Haque A.U., Meng J., Srivastava A.K., Martinez R.: A Novel Hybrid Approach Using Wavelet, Firefly Algorithm, and Fuzzy ARTMAP for Day-Ahead Electricity Price Forecasting, IEEE Transactions on Power Systems, Vol. 28. No. 2, 2013, pp. 1041-1051.
  14. Merayo D., Rodriguez-Prieto A., Camacho A.M.: Comparative analysis of artificial intelligence techniques for material selection applied to manufacturing in Industry 4.0, Procedia Manufacturing no. 41, 2019, pp. 42-49.
  15. Mielczarski W.: Rynki energii elektrycznej. Wybrane aspekty techniczne i ekonomiczne (Eng. Electricity markets. Selected technical and economic aspects), ARE S.A. Warszawa 2000, pages 321.
  16. Moghaddam R.K., Yazdan N. M.: A Comparative Analysis of Artificial Intelligence – Based Methods for Fault Diagnosis of Mechanical Systems, Mechanics and Mechanical Engineering, nr 23, Sciendo, 2019, pp. 113-124.
  17. Mynarski S.: Modelowanie rynku w ujęciu systemowym (Eng. System modeling of the market), PWN, Warszawa, 1982, pages 182.
  18. Nazarko J. [red. nauk.]: Prognozowanie w zarządzaniu przedsiębiorstwem, Cz. 4. Prognozowanie na podstawie modeli trendu (Eng. Forecasting in enterprise management, Cz. 4. Forecasting based on trend models), Oficyna Wydawnicza Politechniki Białostockiej, Białystok, 2018, pages 182.

19. Popławski T., Weźgowiec M.: Krótkoterminowe prognozy cen na Towarowej Giełdzie Energii z wykorzystaniem modelu trendu pełzającego (Eng. Short-term price forecasts on the Polish Power Exchange using the crawling trend model), *Przegląd Elektrotechniczny*, R. 91, Nr 12, 2015, pp. 267-270.
20. Ruciński D.: 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. *Studia Informatica. Systems and Information Technology*. No. 1-2 (23), 2019, pp. 77-93.
21. Ruciński D.: Neural modeling of electricity prices quoted on the Day-Ahead Market of TGE S.A. shaped by environmental and economic factors. *Studia Informatica. Systems and Information Technology*. No. 1-2 (24), 2020, pp. 25-36.
22. Staniszewski R.: Sterowanie procesem eksploatacji (Eng. Control of the operation process), WNT, Warszawa, 1988, pages 475.
23. Tchórzewski J.: Inżynieria rozwoju systemów (Eng. Systems development engineering), WSR-P w Siedlcach, Siedlce 1990, pages 279.
24. Tchórzewski J.: Cybernetyka życia i rozwoju systemów (Eng. Cybernetics of life and systems development), WSRP w Siedlcach, Siedlce 1992, pages 408.
25. Tchórzewski J.: Rozwój system elektroenergetycznego w ujęciu teorii sterowania i systemów (Eng. Development of the power system in terms of control theory and systems), OW PWr, Wrocław 2013, pages 190.
26. Tchórzewski J.: Metody sztucznej inteligencji i informatyki kwantowej w ujęciu teorii sterowania i systemów (Eng. Methods of artificial intelligence and quantum computing in terms of control theory and systems), Wydawnictwo Naukowe UPH, Siedlce 2021, pages 343.
27. Tchórzewski J. and Marłęga R.: The Day-Ahead Market System Simulation Model in the MATLAB and Simulink Environment, 2021 Progress in Applied Electrical Engineering (PAEE), 2021, pp. 1-8.
28. Tchórzewski J., Marłęga R.: Modeling and simulation of the control- and the systems-inspired of the Polish Electricity Exchange, 2017 Progress in Applied Electrical Engineering (PAEE), IEEE Digital Library, 2017, pp. 1-6.

29. Tchórzewski J., Marłęga R., The Management System of the Polish Electricity Exchange from the Viewpoint of the Control and Systems Theory, 16th International Conference on the European Energy Market (EEM), Ljubljana, Slovenia, IEEE Xplore Digital Library, 2019, pp. 1-5.
30. Tchórzewski J., Ruciński D.: Modeling and simulation inspired by quantum methods of the Polish Electricity Stock Exchange, Progress in Applied Electrical Engineering, 2017, pp. 1-6.
31. Trusz M., Tserakh U.: GARCH(1,1) models with stable residuals. *Studia Informatica. Systems and Information Technology*, No. 1-2(22), 2017, pp. 47-57.
32. Voronin S.: Price spike forecasting in a competitive day-ahead energy market. *Acta Universitatis, Lappeenranta University of Technology*, 2013, pages 177.
33. [www.tge.pl](http://www.tge.pl) – Towarowa Giełda Energii S.A. (Eng. Towarowa Giełda Energii Joint-Stock Company), website [access: 2019-2022].