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The impact of the size of the training set on the predictive abilities of neural models on the example of the Day-Ahead Market System of TGE S.A.

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Abstract. The main object of the research was to examine the acceptable time horizon that could be predicted by previously learned models of the Day-Ahead Market (DAM) TGE S.A. system. The article contains the results of research on the predicting ability of different ANN models of the DAM TGE S.A. The research was conducted based on data covering the operation of the Polish stock exchange in the period from 2002 to 2019 (the first half of the year). The research was carried out based on the learned ANN models of the DAM system. Data were taken for examination covering the time from 2002 to 2019 (1st half of the year) and was divided into a different period, i.e., a month, a quarter, and a half-year. , year, etc. The MSE, MAE, MAPE, and R^2 were adopted as the criteria for assessing the ability of individual models to predict electricity prices. The research was carried out by successively expanding forecasting periods in a rolling manner. For example, for a half-year, prediction time intervals were increased from one week to month, two months, quarter, half-year, etc. results for a model representing a given period. A lot of interesting research results were obtained.

Keywords. Day-Ahead Market, MATLAB and Simulink environment, neural modeling, prediction time, electricity prices

1. Characteristics of the research subject

There are various subjects and directions of implementing artificial neural networks as neural models of the system, e.g., for modeling the development of the power system [25], human walking [26], the movement of the end of the robot arm [28], or teaching the Artificial Neural Network neural model as a model of the DAM system [14, 23-24, 27, 29]. The subject of the current paper is the Day-Ahead Market (DAM), into 'Towarowa Giełda Energii S.A.' which is functioning since the almost beginning of this century (2002). The quotations on the Day-Ahead Market concern delivered and sold electricity and the resulting volume-weighted average unit price of electricity obtained in each hour of the day [14-18, 24, 31].

Data for the conducted research experiments were obtained from Towarowa Giełda Energii S.A. from 2002-2019 as data on hourly quotes [31]. The model of the DAM system depends on many factors affecting the volume of electricity, such as weather factors: temperature, insolation, wind speed, air humidity, etc. All of them have a significant impact on the demand for the volume of electricity per hour of the day and the volume-weighted average price of energy. It is worth emphasizing here that the research concerns multi-input and multi-output (MIMO) systems and their neural models, i.e., models with 24 inputs related to the volume of electricity and 24 outputs related to the volume-weighted average electricity price in particular hours of the day [22-23]. The examined neural models concern the setting of prices [PLN] on the DAM as an output of the model depending on the supplied and sold volume of electricity in particular hours of the day [MWh] as an input of the model. The research considered the influence of the data quotation period on the quality of ANN was published by the author in [14]. The general conclusion of that paper was that a half-year period (181 data sets) was chosen as suitable.

There are many concepts for the construction of artificial neural networks and methods of teaching them, from unidirectional multilayer networks [7, 12, 19-20, 30], to single-layer neural networks with feedback [8, 12, 30] and cellular neural networks [5, 7, 12, 19-20, 23, 30], as well as deep [13], ontogonic or with architecture optimization [4, 11] and chaotic [6] neural networks, up to special networks such as networks evolving neural [29]. The research on the influence of the chosen type of ANN on the model quality was published by the author in [15] in which the Perceptron ANN was chosen for further work. The undertaken research aims to evaluate the obtained Perceptron neural models in the ability of prediction.

One of the important problems in this respect, concerning the subject of the research, is the determination of the length of the prediction period for subsequent models of the DAM system in terms of its ability to predict the price of electricity in a given hour of the day [14-15]. The

Artificial Neural Network was selected for the construction of the DAM system, due to its properties used in approximation. It is a fairly commonly used tool for designing and teaching models in the form of artificial neural networks. From among the many available types of existing artificial neural networks, a multi-layer, unidirectional neural network called Perceptron ANN was finally selected [2, 7, 9, 12, 19-21, 30].

An important issue in the conducted research was the construction of neural models of the Day-Ahead Market system, with the use of which simulation and comparative studies were carried out [14-17, 27]. To verify the correctness of neural models, several research experiments, including prognostic studies, have been developed. To determine both the acceptable prediction period for a given model and answer the question of whether the number of training and testing pairs used to design and train the TGE S.A. DAM system has a significant impact on the quality of electricity price prediction.

Models of the Day-Ahead Market system were built in the environment of MATLAB and Simulink [1, 14-17], which were used in the research due to the orientation of this environment for conducting scientific and engineering research. There are other considered research environments such for example, SPHINX, SAS, or SAP. In the final process of selecting the computing environment for research, technical considerations (availability of the tool) and its functional characteristics, were taken into account. The advantages of choosing a tool that was taken into consideration are the possibility of using numerous functions to support research with the use of various libraries. The quality of the model is understood as the degree of fit, the ability to generalize, and the learning time, which largely depends on the training algorithms. The Levenberg-Marquardt algorithm was chosen as a relatively often used algorithm for training system models in the MATLAB environment, which is characterized by high speed and accuracy of learning as well as high quality of the models obtained [3, 7, 10].

1.1. Implementation of ANN

As a base for further examination, the Perceptron ANN was chosen. The architecture of the used ANN was shown in Fig. 1. The Levenberg-Marquardt algorithm was used to train the neural model of the DAM system and implemented in the MATLAB and Simulink environment. One of the basic functions used in training is the trainlm() function which supports training with validation and test vectors. One of its properties, i.e., net.divideFcn(), is set to dividerand() by default, which causes a random data division in the following proportions: 70% training data, 15% validation data, and 15% testing data. It is possible to define the proportions division of the data set by defining the following properties: net.divideParam.trainRatio(), net.divideParam.valRatio(), and net.divideParam.testRatio().

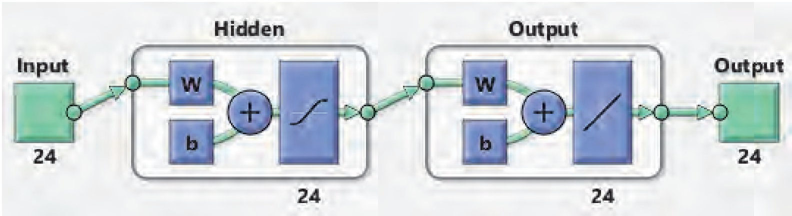


Figure 1. Perceptron ANN architecture is taught in the DAM neural model. Markings: Input (24) - input signals to ANN, here: the amount of electricity supplied and sold in each hour of the day (24 signals), Hidden - hidden layer model in which the weight matrix (W) and the bias vector (b) are distinguished,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

Validation vectors are used to stop the learning process early and then defined into network property. If the network performance measured by the validation vector values does not improve or remains the same for a certain number of epochs specified in the max_fail() property, the training process is stopped. The test vectors are only used to check whether the neural network is not over-learned, i.e., whether it generalizes well the learned model by checking on pairs that did not participate in the learning process, so the test data does not have any influence on the process of learning of the system model, but performs the control function.

Neural network training ends when any of the following conditions occur :

1) the maximum number of epochs (repetitions) has been reached,
2) the maximum learning time has been exceeded,
3) the error is understood as the difference between the target value and the value obtained from the model has reached the assumed minimum value,
4) the performance gradient has dropped below the value specified in *min_grad*,
5) the value of mu has exceeded the value specified in the *mu_max* variable,
6) the error value in the validation process has increased more times than the value specified in *max_fail* times since the last decrease.

2. Research experiments

Data for assessing the quality of the Perceptron ANN was previously prepared by teaching various artificial neural networks with the use of various data sets collected from the entire period of the TGE S.A. DAM from 01.07.2002 to 30.06.2019 [14, 31]. The entire period has been divided into smaller periods that can be used in ANN training with different lengths of measurement samples as shown in Tab. 1, i.e., a period of one month, a quarter and a half-year up to 5 years, 10 years with a step of one year and 15 years with a step of one year.

Table 1. Possibilities of training ANN with the use of data from periods with different possible lengths of quotations on the TGEE DAM. Source: own study.

Period	The number of learning subsets	The number of days
month	204	30
quarter	68	90
half-year	34	180
year	17	365
2 years	8	730
3 years	5	1095
4 years	4	1460
5 years	3	1825
10 years in steps of 1 year	8	3650
15 in steps of 1 year	3	5475

As a result of the division of data into different research periods, a total of 354 data sets were obtained, which were the basis for teaching 354 artificial neural networks, respectively, of neural models and, on their basis, for conducting various types of simulation studies.

Simulation studies relayed on in assessing the predictive abilities of individual neural models from a given period. Each individual set of models, month, quarter, year, etc. was treated as a base for examination and the prediction period. It was moved forward by a specific time interval for each iteration. In each integration predictive period was longer concerning the examined model.

In this way, the given neural model simulated the period which, in subsequent iterations, modeled the volume-weighted average electricity prices in particular hours of the day on the DAM TGE S.A. It establishes the possibility of an increasingly longer predictive range (forecasting in the more and more distant future concerning the base model). Tab. 2 shows the courses of successive periods for individual models.

Table 2. Assumptions adapted to carry out the ANN model quality research for individual data sets. Source: own study.

Period	Timeshift in days	Number of cycles
month	2	10
quarter	7	10
half-year	12	10
year	24	10
2 years	48	10
3 years	72	10
4 years	96	10
5 years	120	10
10 years in steps of 1 year	120	7
15 in steps of 1 year	180	5

For research purposes, it was assumed that the predictive abilities of a given neural model are tested up to 60% of the studied period for which the neural model was taught, and the individual steps are proportional to the model learning period. Constant-step studies were also carried out, i.e., for one week period for all data sets, however, due to the volume of the article, the results of the research were omitted. The assessment of predictive abilities was based on such measures and indicators:

1) mean square error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i^s - y_i^n)^2 , \tag{4}$$

where:

y_i^n - value of the i-th output quantity of the model,

y_i^s - value of i-th system output quantity,

2) regression indicator (R^2),

$$R^2 = \frac{\sum_{i=1}^{n}(y_i^n - \overline{y^n})^2}{\sum_{i=1}^{n}(y_i^s - \overline{y^s})^2} , \tag{5}$$

where:

$\overline{y^n}$- mean value of the output value of the model,

$\overline{y^s}$- mean value of the system output.

3) mean absolute percentage error (MAPE)

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i^s - y_i^n}{y_i^s}\right| , \tag{6}$$

4) mean absolute error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i^s - y_i^n| , \tag{7}$$

as well as the analysis of the obtained test results was also carried out based on:

5) mean standard deviation:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(y_i^n - \overline{y^n})^2}{n-1}} , \tag{8}$$

As a result of the conducted research, many important results were obtained, including concerning the possibility of determining the forecast length for learned models.

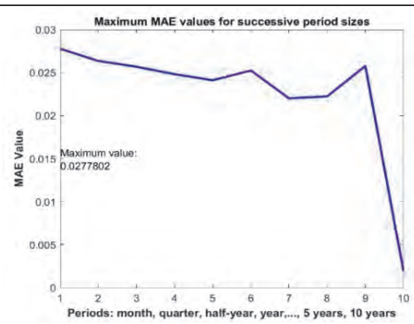
3. Results of experimental research

As a result of the conducted experimental research, several significant test results were obtained, which were summarized for the mean MSE and MAE error value, for ANN models, individual data sets, and individual prediction periods, in Tab. 3, and for the value of index R^2 and MAPE for ANN models, for individual data sets and individual prediction periods in Tab. 4. On the other hand, the values of the mean standard deviation of the MSE and MAE are shown in Tab. 9 as well as regression index R^2 and MAPE are shown in Tab. 10.

The obtained test results concerning the course of MSE errors and MAE errors for individual prediction period lengths, summarized in Tab. 3, showed that the minimum, mean and maximum values of the MSE error decrease with the increase of the data set to a certain value, in this case, it is the value corresponding to the periods of 2 - 3 years old. It is also worthy to notice the significant decrease in the MAE error for the last 10-year period, which is dictated by the division of this period into a smaller number of periods. It does not simulate proportionally the same period used for prediction as shorter periods.

When analyzing the prediction waveforms for individual periods, it can be concluded that the waveforms of both the MSE error measure and the MAE error measure behave similarly, error values are similar for all periods and increase with the extension of the predicted simulation period, which seems obvious because the value of the increased error of both MSE and MAE is essentially quasi-linear concerning the distinguished periods.

Table 3. Values of the average MSE for ANN models for given data sets and individual prediction periods (described in Tab. 2). Source: own study.

Description of diagram	MSE error	MAE error
The course of **maximum errors** of MSE and IEA for subsequent periods from one month, quarter, half-year, year, 2 years 3 years, 4 years, 5 years, 10 years, and 15 years of the DAM operation under study		

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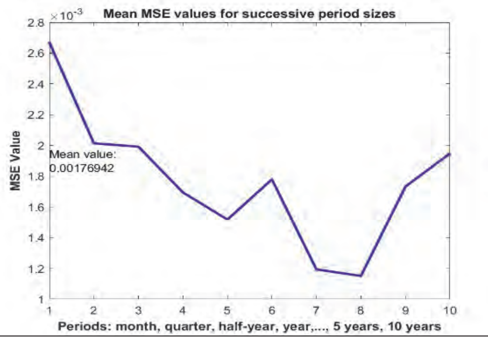
<td>
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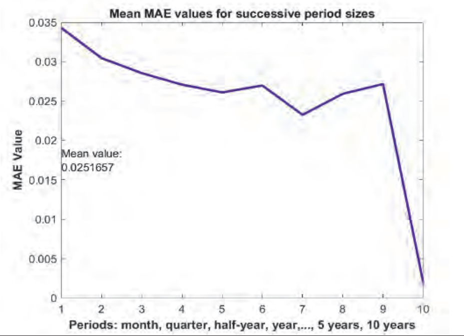
<td>
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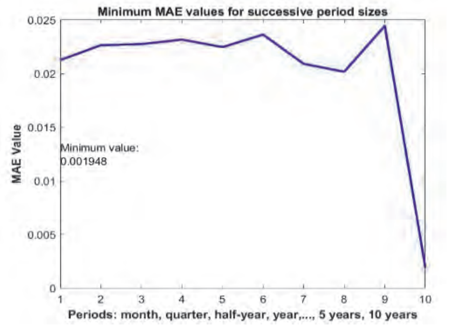
<td>
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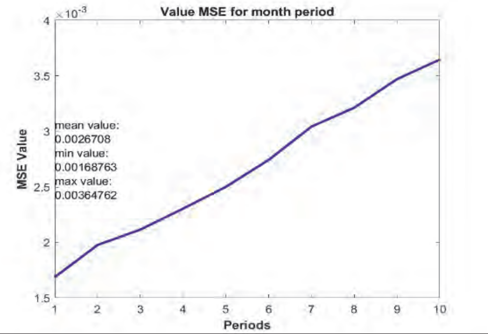
<td>
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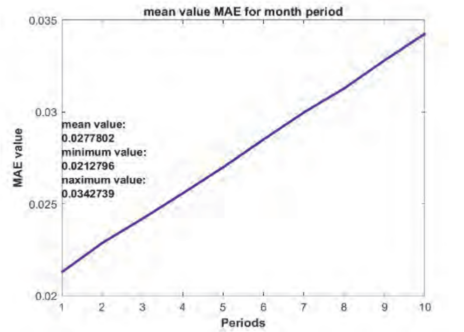
<td>
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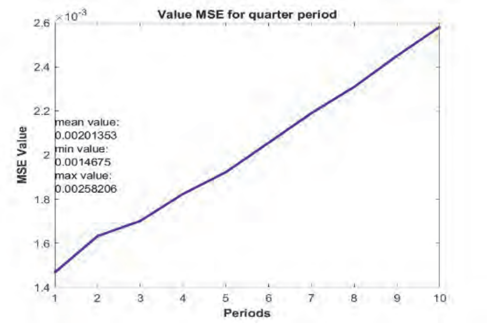
<td>
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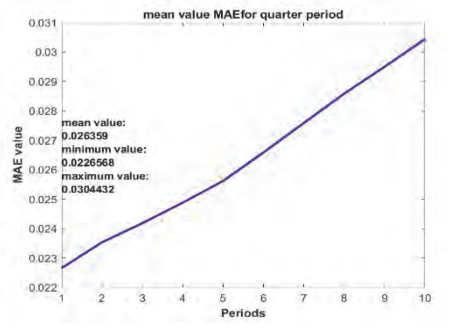
<td>
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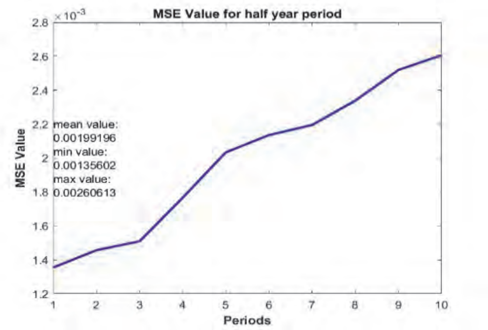
<td>
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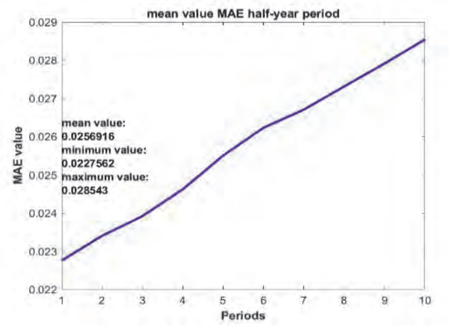
<td>
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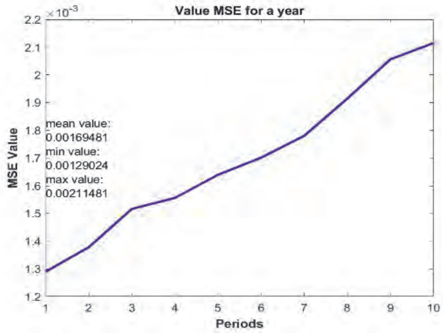
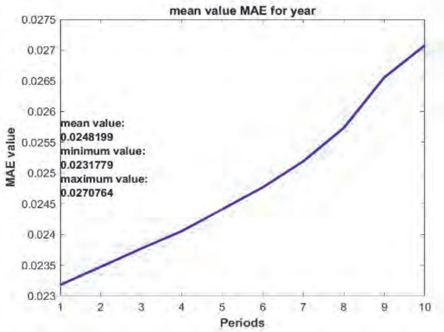
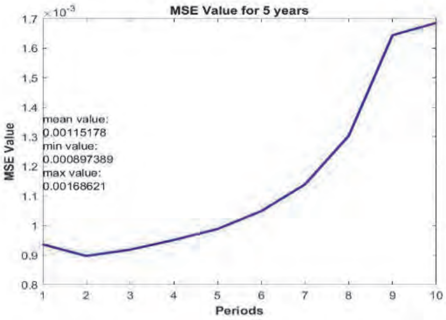
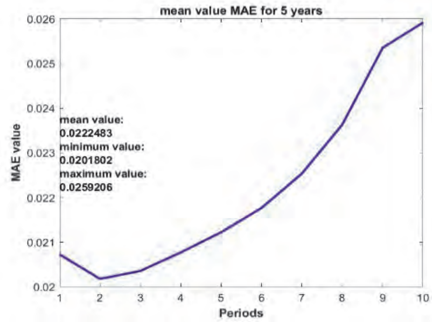
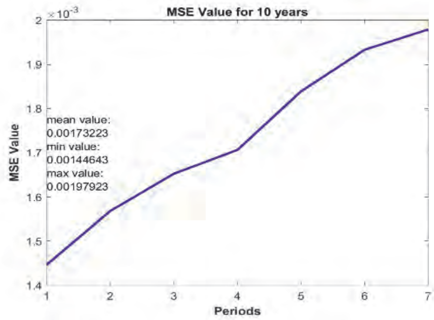
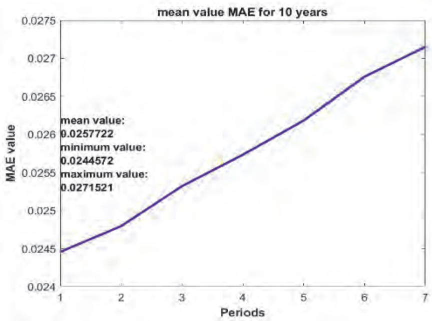
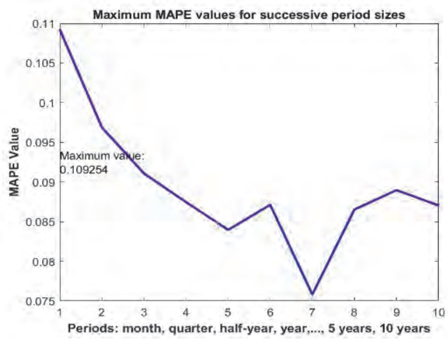
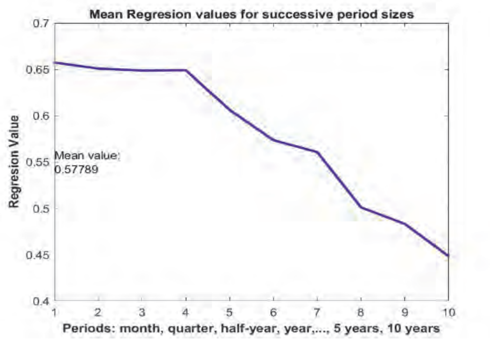
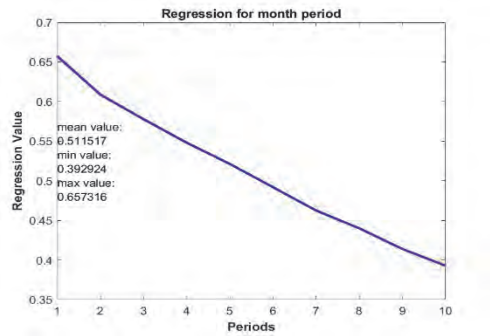
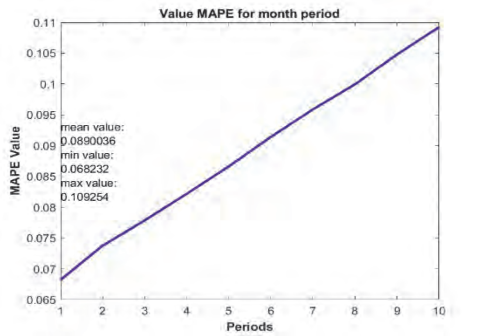
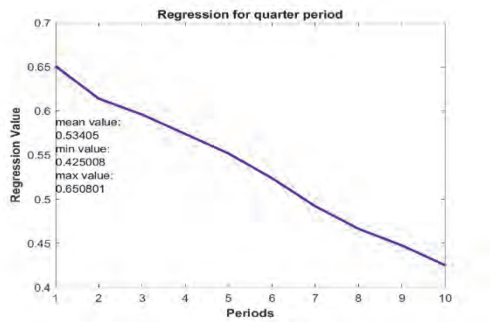
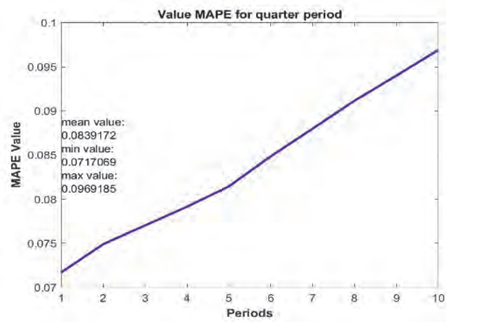
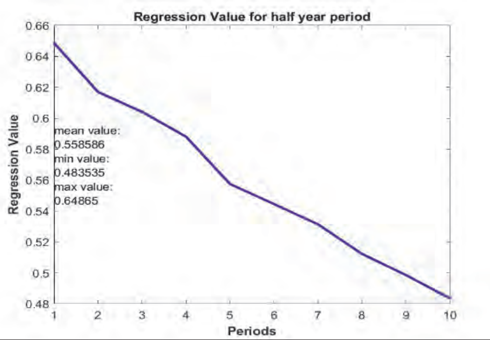
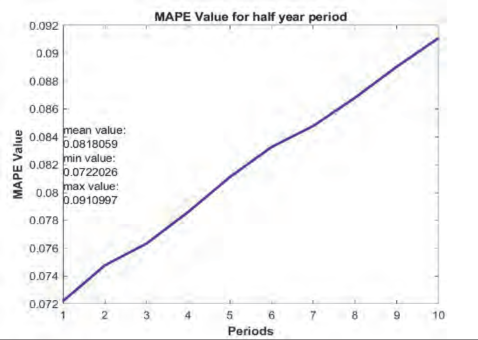
The course of MSE and MAE errors **for year periods**, taking into account successive period shifts from Tab. 2		
The course of MSE and MAE errors **for 5-year periods**, taking into account subsequent period shifts from Tab. 2		
The course of MSE and MAE errors **for 10-year periods**, taking into account subsequent period shifts from Tab. 2		

Table 4. The values of the average regression index R^2 and MAPE for ANN models for given data sets and individual prediction periods(described in Tab. 2). Source: own study.

Description of diagram	**Regression R^2 error**	**MAPE error**
The course of the **maximum regression index and MAPE** for subsequent periods from one month, quarter, half-year, year, 2 years, 3 years, 4 years, 5 years, 10 years, and 15 years of the DAM operation under study		

The course of the **average regression index and MAPE** for subsequent periods from one month, quarter, half-year, year, 2 years, 3 years, 4 years, 5 years, 10 years, and 15 years of the DAM operation under study		
The course of the **minimum regression index and MAPE** for subsequent periods from one month, quarter, half-year, year, 2 years, 3 years, 4 years, 5 years, 10 years, and 15 years of the DAM operation under study		
The course of the **regression index and MAPE for monthly periods**, taking into account the successive shifts of the periods from Tab. 2		
The course of the **regression index and MAPE for quarter periods**, taking into account the successive shifts of the periods from Tab. 2		
The course of the **regression index and MAPE for half-year periods**, taking into account the subsequent period shifts from Tab. 2		

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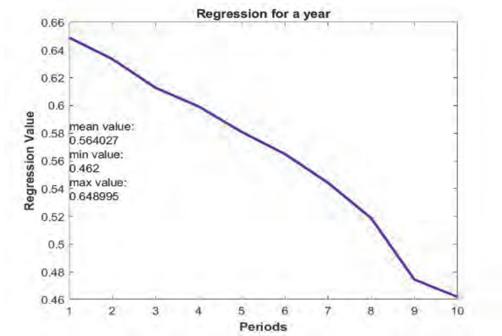
<td>
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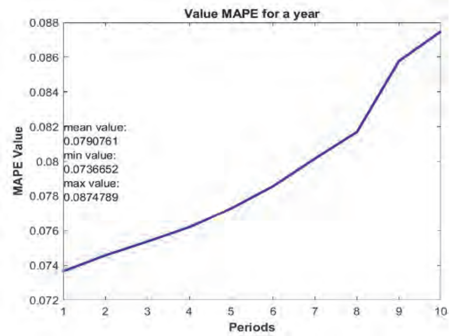
<td>
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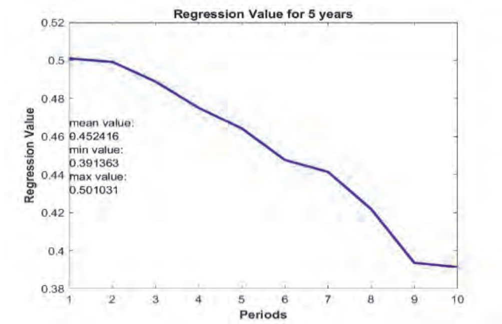
<td>
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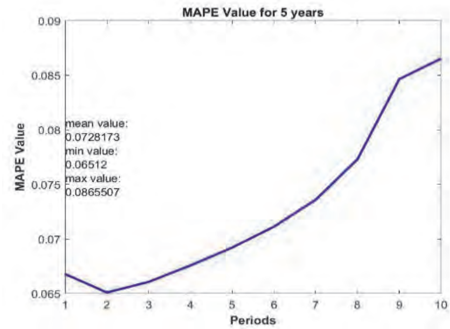
<td>
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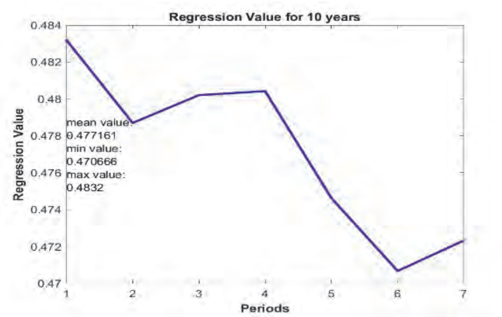
<td>
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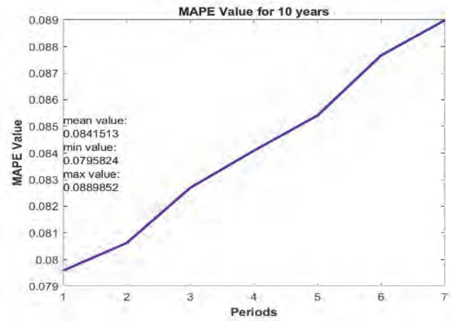
<td>
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The results of the analysis in Tab. 4 of the waveforms show that the values of the minimum, average, and maximum of R^2 regression coefficients indicate relatively compared to other periods high value. The best quality of prediction for given models is achieved for the period of half a year and one year (0.56-0, 57). In the case of the MAPE index, the optimal period is shifted concerning the value of the R^2 index, in this case, it is the size of the set corresponding to periods of 2-3 years and equals 0.076-0.062. However, the values of the MAPE index for the semi-annual period are already satisfying 0.075-0.082, their value is relatively low compared to other models, which means a better quality of the simulated prediction.

When analyzing the forecast curves for individual periods, it can be noticed that both the regression index R^2 and the MAPE index behave very similarly, i.e., with the increase of the forecast period of the prediction, the value of the regression index decreases, and the value of the MAPE index increases. The error values are similar for all periods, however, as the set of data (longer period) increases, the mean regression values decrease but the differences between the maximum and minimum values decrease (the 10-year period is an exception, however, as, in the case of MSE and MAE, it did not forecast a sufficiently long period in the future due to the set of available data). When analyzing the course, taking into account the successive shifts of the periods for the MAPE indicator, it can be concluded that it shows no dependence on the length of the forecast period as it is in the case of the R^2 indicator.

3.1. Assessment of the prognostic abilities of models

Selected models were assessed, and the following values were adopted as the evaluation criteria for the regression index:

- ideal forecast -1 ÷ 0.90,
- optimal forecast - 0.60 ÷ 0.89,
- acceptable forecast - 0.50 ÷ 0.59,
- forecast unacceptable - below 0.50.

Taking into account the adopted evaluation criteria and the obtained mean regression of the values for a given period (Tab. 5), the assessment of predictive abilities (in days) of the examined models can be presented in Tab. 6.

Table 5. Numerical values of the average regression index R^2 for ANN models for individual data sets and individual prediction periods. Columns show the mean R^2 value for incising prediction periods (for months 2,4,6, …, and 20 days). Source: own study.

The size of the ANN model	period [days]	Mean Regression Value									
Month	2	0.65732	0.60884	0.57781	0.54817	0.52133	0.49202	0.46256	0.44015	0.41404	0.39292
Quarter	7	0.65080	0.61391	0.59587	0.57384	0.55164	0.52374	0.49190	0.46630	0.44750	0.42501
Half-year	12	0.64865	0.61699	0.60419	0.58808	0.55752	0.54454	0.53142	0.51232	0.49862	0.48353
Year	24	0.64899	0.63352	0.61282	0.59934	0.58093	0.56507	0.54427	0.51875	0.47456	0.46200
2 years	48	0.60628	0.59307	0.58093	0.55552	0.52645	0.51797	0.51285	0.50551	0.49683	0.46458
3 years	72	0.57356	0.56217	0.52953	0.50987	0.49677	0.49173	0.48845	0.48687	0.47930	0.48045
4 years	96	0.56073	0.54660	0.52698	0.51833	0.51505	0.50136	0.48711	0.46703	0.45290	0.43018
5 years	120	0.50103	0.49922	0.48888	0.47503	0.46425	0.44766	0.44138	0.42181	0.39354	0.39136

Moreover, the predictive ability was assessed concerning the ANN model size according to the following relationship. The prediction coefficient (WsP) that determines the predictive ability of the model:

$$WsPi = \frac{nd}{wm}, \tag{9}$$

where:

nd – number of prediction days for a given criterion (perfect forecast, optimal forecast, acceptable forecast, inadmissible forecast),

wm - the size of the ANN model (data from Tab. 1).

i – index taken value: p (perfect), o (optimal), a (acceptable).

This indicator helps to estimate the predictive ability of the model concerning the size of the training set for given evaluation criteria. For example, the 6-day prediction horizon for the monthly training set is not comparable to the annual set of learning data.

Table 6. Assessment of the predictive abilities of models according to the regression index R^2. Source: own study.

The size of the SSN model (nd)	perfect forecast [days]	WsPp	optimal forecast [days]	WsPo	Acceptable forecast [days]	WsPa	inadmissible forecast [days]
Month	0	0	4	0.13	20	0.67	More than 20 days
Quarter	0	0	14	0.16	42	0.47	More than 42 days
Half-year	0	0	36	0.2	96	0.53	More than 96 days
Year	0	0	72	0.19	192	0.53	More than 192 days
2 years	0	0	48	0.07	384	0.53	More than 384 days
3 years	0	0	0	0	288	0.27	More than 288 days
4 years	0	0	0	0	576	0.40	More than 576 days
5 years	0	0	0	0	120	0.07	More than 120 days

It can be noticed (Tab. 6) that the best WsP coefficient, taking into account R^2, for optimal forecasts is characteristic for the six-month periods (WsP index - 0.2). The period of one year also has a high value of the WsP index - 0.19, relatively to other periods. The remaining periods are characterized by worse rates or a zero index. For the acceptable forecast, there is a clear relationship between the size of the model and the value of the indicator. from 0.67 for a month to 0.07 for five years. Considering the above, it can be concluded that the six-month period is optimal from the point of view of the adopted criteria.

The selected models were also assessed by the MSE value. The following ranges have been adopted:

- ideal forecast –0 ÷ 0.0001,
- optimal - 0.0002 ÷ 0.002,
- acceptable forecast - 0. 0021 ÷ 0. 0026,
- inadmissible forecast - above 0. 0026.

Table 7. Numerical values of the average MSE for ANN models for individual data sets and individual prediction periods. Columns show the mean MSE value for incising prediction periods (for months 2,4,6, …, and 20 days). Source: own study.

The size of the SSN model	period [days]	Mean MSE Value									
Month	2	0.00169	0.00198	0.00212	0.00230	0.00250	0.00274	0.00304	0.00321	0.00347	0.00365
Quarter	7	0.00147	0.00163	0.00170	0.00182	0.00192	0.00206	0.00219	0.00231	0.00245	0.00258
Half-year	12	0.00136	0.00146	0.00151	0.00177	0.00203	0.00214	0.00220	0.00234	0.00252	0.00261
Year	24	0.00129	0.00138	0.00152	0.00156	0.00164	0.00170	0.00178	0.00191	0.00206	0.00211

2 years	48	0.00119	0.00128	0.00129	0.00140	0.00154	0.00159	0.00161	0.00165	0.00171	0.00193
3 years	72	0.00145	0.00148	0.00164	0.00174	0.00182	0.00186	0.00188	0.00192	0.00198	0.00201
4 years	96	0.00092	0.00099	0.00123	0.00127	0.00129	0.00147	0.00153	0.00159	0.00177	0.00189
5 years	120	0.00094	0.00090	0.00092	0.00095	0.00099	0.00105	0.00114	0.00130	0.00164	0.00169

Table 8. Assessment of the predictive abilities of models according to the MSE error. Source: own study.

The size of the SSN model (nd)	**perfect forecast [days]**	**WsPp**	**optimal forecast [days]**	**WsPo**	**Acceptable forecast [days]**	**WsPa**	**inadmissible forecast [days]**
Month	0	0	4	0.13	10	0.3	over 10 days
Quarter	0	0	35	0.39	63	0.7	over 63 days
Half-year	0	0	48	0.26	108	0.60	over 108 days
Year	0	0	192	0.53	240	0.67	no data
2 years	0	0	480	0.66	no data	-	no data
3 years	0	0	657	0.6	720	0.65	no data
4 years	0	0	960	0.66	no data	-	no data
5 years	0	0	1200	0.66	no data	-	no data

The assessment of WsP for the predictive abilities of the model based on the MSE measure is ambiguous due to the lack of data for the acceptable forecast. But based on the optimal forecast column, it can be concluded that there is a clear indication that the mean MSE decreases with the increase of the size of the model. The WsP coefficient is the highest at the level of 0.66 for two-year periods.

For the acceptable forecast column, the WsP index, except for the monthly period, shows a similar value in the range of 0.6 ÷ 07. It is also worthily noting that the three periods, i.e., two-years, four-years, and five-year, for the acceptable forecast criteria could not be estimated. In general, for the MSE value the WsP index increases as the model size increases.

Table 9. Mean Standard Deviation MSE and MAE values for ANN models for individual data sets. Source: own study.

Period	**Mean standard deviation for MSE**	**Mean standard deviation for MAE**
month	0,000663	0.0043452
quarter	0,000368	0.0026306
half-year	0,000449	0.0019778
year	0,000275	0.0013103
2 years	0,000229	0.0012649
3 years	0,000198	0.0011780
4 years	0,000202	0.0009329
5 years	0,000297	0.0020752
10 years in steps of 1 year	0,000195	0.0009945

Table 10. Values of the mean standard deviation of the regression index R2 and MAPE for ANN models for individual data sets. Source: own study.

Period	Mean standard deviation for R^2	Mean standard deviation for MAPE
month	0.08692	0.013629
quarter	0.07570	0.008482
half-year	0.05454	0.006300
year	0.06395	0.004695
2 years	0.04608	0.004359
3 years	0.03410	0.004061
4 years	0.02185	0.003600
5 years	0.04056	0.007700
10 years in steps of 1 year	0.07570	0.003482

The values of the mean standard deviation for the measures MSE, MAE, and indicators R^2 and MAPE indicate, that with the extension of the period when the size of the set increases, the deviation decreases in the case of the MAE measure and the MAPE index. For the MSE measure and the regression index R^2 there is no such relationship.

4. General conclusion

The conducted research was aimed to determine the acceptable time horizon, predictable based on the learned neural models of the DAM TGE S.A. system. It is always the question of what an “acceptable horizon” means. To assess the quality of the model same assumptions must be taken. In the case of this research four categories of assessment were taken for the two most commonly used measures (MSE and R^2). Taking into account that for the assessment of a given group of models (monthly, quarterly, etc.), the absolute measure of the number of days is inadequate the WsP coefficient was introduced. It allows to evaluate of a given predicted time horizon concerning the model’s length.

Determining the acceptable prediction period depends on the criterion that will be adopted for individual measures and indicators. By adopting the criteria as in this work, based on the research carried out, it is possible to determine the maximum period that is possible to predict for a given model and to choose the size of the set for which the model is acceptable (according to the adopted criteria). Assuming the described criteria and the values of the WsP index (which is based on exploring MSE and R^2) it can be stated that the optimal prediction period is a one-year or six-month period, for which WsP accounted for the R^2 index was 0.19 and 0.2, respectively, and WsP accounted for MSE it was 0.53.

References

1. Beale M. H. [at all], Neural Network Toolbox™ User's Guide. by The MathWorks. Inc. 1992-2019.
2. Faliński M., Wstęp do sztucznej inteligencji. WN PWN. Warszawa 2020, pages 332.
3. Hagan M.T. and Menhaj M., Training feedforward networks with the Marquardt algorithm. IEEE Transactions on Neural Networks. Vol. 5. No. 6/1999. pp. 989–993.
4. Jankowski N., Ontogeniczne sieci neuronowe. O sieciach zmieniających swoją strukturę. AOW EXIT. Warszawa 2003, pages 312.
5. Kłopotek M., Tchórzewski J., The Concept of Discoveriesin Evolving Neural Net. Advances in Soft Computing. Vol. 17. Wydawnictwo IPI PAN. Warszawa 2002, pp. 165-174.
6. Kosiński R. A., Sztuczne sieci neuronowe. Dynamika nieliniowa i chaos. WNT. Warszawa 2002, pages 195.
7. Korbicz J., Obuchowicz A., Uciński D., Sztuczne sieci neuronowe. Podstawy i zastosowania. Problemy Współczesnej Nauki. Teoria i zastosowania. Informatyka. AOW PLJ. Warsza*wa 1994, pages 251.
8. Mańdziuk J.: Sieci neuronowe typu Hoppfielda. Teoria i przykłady zastosowań. AOW EXIT. Warszawa 2000, pages 262.
9. Marecki J., Metody sztucznej inteligencji. WSIiZ. Bielsko-Biała 2001, pages 115.
10. Marquardt D., An Algorithm for Least-Squares Estimation of Nonlinear Parameters. SIAM Journal on Applied Mathematics, Vol. 11. No. 2/1963, pp. 431–441.
11. Obuchowicz A., Patan K., Sieć neuronów dynamicznych jako generator residuów. Optymalizacja architektury. Materiały III Konferencji nt. "Diagnostyka procesów przemysłowych", Gdańsk-Jurata 1998, pp. 101-106.
12. Osowski S., Sieci neuronowe do przetwarzania informacji, OW PW, Warszawa 2013. pages 422.
13. Patterson J., Gibson A., Deep Learning. Praktyczne wprowadzenie, Helion, Warszawa 217, pages 451.

14. Ruciński D., Data Quotation Period and the Quality of ANN Learning in the Polish Power Exchange Model. [in: et al.] Uncertainty and Imprecision in Decision Making and Decision Support: New Advances, Challenges, and Perspectives. IWIFSGN BOS/SOR 2020 2020. Lecture Notes in Networks and Systems, Vol 338. Springer, Cham. https://doi.org/10.1007/978-3-030-95929-6_24 [Access: 2022].

15. Ruciński D., The Influence of the Artificial Neural Network Type on the Quality of Learning on the Day-Ahead Market Model at Polish Electricity Exchange Join-Stock Company, Studia Informatica. System and Information Technology, Vol. 1-2(23)2022, pp. 77-93.

16. Ruciński D. Tchórzewski J., Neural modeling of the electric power stock market in the usage of MATLAB and Simulink tools for the day ahead market data. Journal of Information System in Management. Vol. 5 (2) 2016 pp. 215-226.

17. Ruciński D., Neural-evolutionary Modeling of Polish Electricity Power Exchange. Electrical Power Networks. EPNet. Katedra Energoelektryki PWr., Institute of Power Engineering and Control Systems of Lviv Polytechnic National University. Ukraine and O/Wrocławski SEP. XPlore Digital Library, Szklarska Poręba 2016 r., pp. 1-6.

18. Ruciński D.. Kłopotek M.. Tchórzewski J., Self-Organizing Wireless Ad-hock Sensor Networks. Studia Informatica. Systems and Information Technology. Volume: 1(5)2005, pp. 69-80.

19. Rutkowska D., Piliński M., Rutkowski L., Sieci neuronowe. algorytmy genetyczne i systemy rozmyte, WN PWN, Warszawa – Łódź 1997, pages 411.

20. Rutkowski L., Metody i techniki sztucznej inteligencji, WN PWN, Warszawa 2020, pages 435.

21. Tadeusiewicz R., Korbicz J., Rutkowski L., Duch W., Sieci neuronowe w inżynierii biomedycznej. Seria: Inżynieria biomedyczna. Podstawy i zastosowania, tom 9. AOW EXIT. Warszawa 2021, pages 746.

22. Tadeusiewicz R., Biocybernetyka. Metodologiczne podstawy dla inżynierii biomedycznej, WN PWN, Warszawa 2013, pages 232.

23. Tchórzewski J., Metody sztucznej inteligencji i informatyki kwantowej w ujęciu teorii sterowania i systemów, WN UPH, Siedlce 2021, pages 343.

24. Tchórzewski J., Neural networks for processing knowledge about the electric energy market, Poznan University of Technology Academic Journals. Electrical Engineering, Vol. 53/2007, pp. 51-63.

25. Tchórzewski J., Roman P., Żurawski T., Modelowanie neuronalne rozwoju systemu elektroenergetycznego na bazie danych testowych IEEE RTS. Wiadomości Elektrotechniczne. Wydawnictwo SIGMA NOT. Tom R. 82. Nr 2/2014. pp. 17-23.

26. Tchórzewski J., Wielgo A., Neural model of human gait and its implementation in MATLAB and Simulink Environment using Deep Learning Toolbox. Studia Informatica. Systems and Information Technology. Vol. 1-2(25)2021, pp. 39-66.

27. Tchórzewski J., Ruciński D., Evolutionary-Supported and Quantum-Inspired Neural Modeling Applied to the Polish Electric Power Exchange. 2019 Progress in Applied Electrical Engineering (PAEE), IEEE Digital Library, pp. 1-8. 2019.

28. Tchórzewski J., Ruciński D., Domański P., Artificial neural network inspired by quantum computing solutions using the movement model of the PR-02 robot, ITM Web of Conferences 19. 01007 (2018). https://doi.org/10.1051/itmconf/ 20181901007. pp. 1-2 2018 [Access: 2021].

29. Tchórzewski J., Kłopotek M., A case study in neural network evolution. Prace Instytutu Podstaw Informatyki Polskiej Akademii Nauk, No 943/2001. pp. 1-12.

30. Żurada J., Barski M., Jędruch W., Sztuczne sieci neuronowe. Podstawy teorii i zastosowania, WN PWN, Warszawa 1996, pages 375.

31. www.tge.pl, strona internetowa Towarowej Giełdy Energii S.A. [dostęp: lata 2017-2022].