DATA QUOTATION PERIOD AND THE QUALITY OF ANN LEARNING AS A POLISH POWER EXCHANGE MODEL

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Agenda

- Introduction to Polish Electricity Power Exchange
- The problem of the number of learning pairs
- Characteristic of the MLP
- Data used in calculations and market characteristics
- Tools and method of modeling
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- Conclusions and directions for further research
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Introduction to Polish Electricity Power Exchange

- Modeled system is Polish Electricity Power Exchange for the Day Ahead Market:
  - 24 input quantities represent the total volume of all transactions on the trading session for a given hour of the day [MWh].
  - 24 output quantities representing the volume weighted average price of all transactions on the trading session for a given hour of the day [PLN / MWh].

The problem of the number of learning pairs

The main target of the research was to find out the quality of Artificial Neural Network (ANN) as multidimensional approximation of the Polish Electrical Power Exchange (PEPE) Day Ahead Market (DAM) model.

The data used for modeling covers the entire period of functioning of the Polish stock exchange from 2002to 2019.

The problem is to find the length of period of the data to model DAM system.

As a measure of the quality of the model the MSE and coefficient of determination R^2 was taken.

Period	Number of learning subsets
month	204
quarter	68
half-year	34
year	17
2 years	8
3 years	5
4 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 years in steps of 1 year	3
The entire period under study, 01/07/2002 - 30/06/2019	1

- Due to the relatively large set of data used in this case to teach ANN, i.e. 17.5 years.

The data was divide into different research periods in order to determine the quality of the approximation in the ANN learning process.

Characteristic of the MLP

As a tool for examining ANN network was used:

- ANN perceptron model,
- Back-propagation method,
- Levenberg-Marquardt teaching algorithm,
- Two layers network function of the activation
- *tansig* as a first layer activated function,
- *purelin as a second layer activation function,*
- Quality of model was measured by the mean square error MSE and R^2.

Tools and method of modeling

- MATLAB and Simulink environment was chosen for the ANN design and learning process.

The experiments run as follows:

- Designing the ANN architecture, in this case using the feedforwardnet (hiddenSizes, trainFcn) function, which has two optional arguments: hiddenSizes (number of neurons in hidden layers),
- trainFcn ANN training function,
- Determining the arguments of the net. for retrieving input and output values (so-called training pairs, testing pars, validating pars),
- ANN training parameters, including methods of initialization of initial weights and bias values,
- re-initialization of weights was performed by the init (net) function.

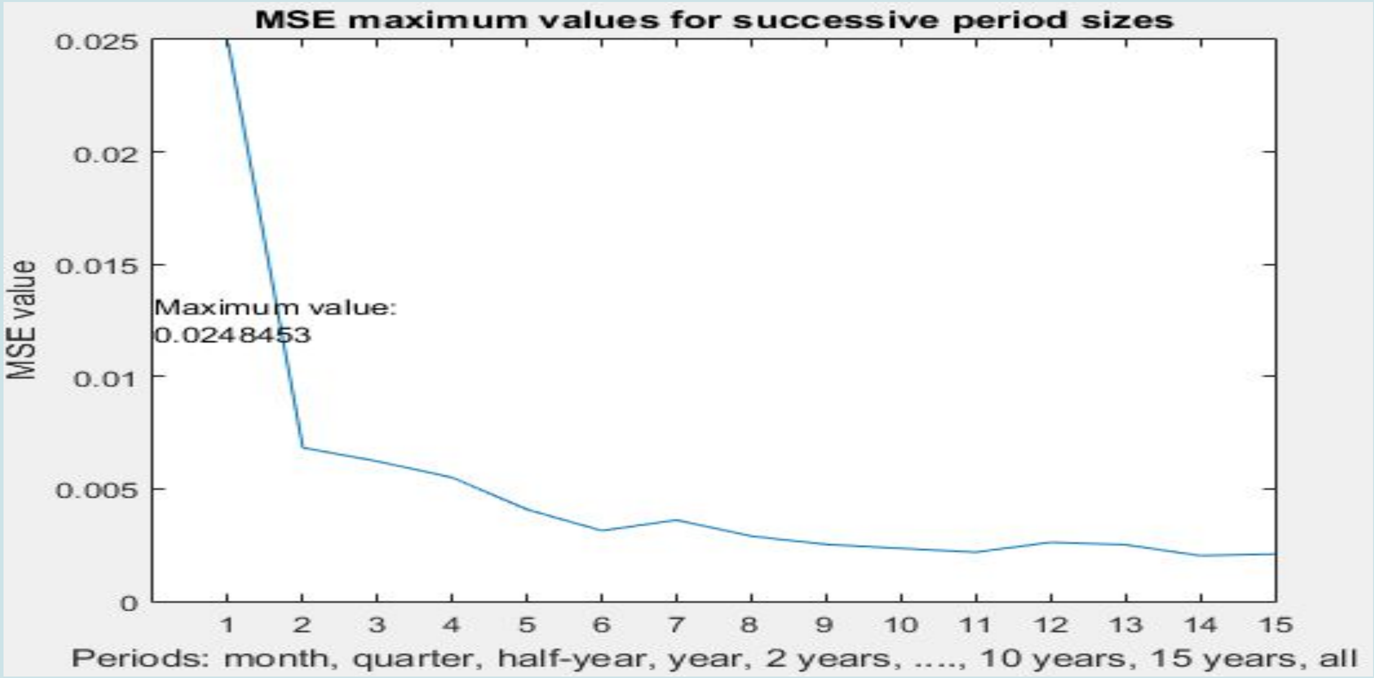
Modeling results for the MSE error value obtained for the Perceptron ANN

The obtained values for the appropriate length of modeling periods			
The length of the quotation period on the PPE DAM	maximum	minimal	mean
month	0,024845	2,49E-12	0,000727
quarter	0,006832	7,29E-05	0,000907
half-year	0,006224	0,000209	0,001114
year	0,005502	0,000326	0,001377
2 years	0,00408	0,00044	0,001615
3 years	0,003139	0,00064	0,001338
4 years	0,003612	0,000603	0,001552
5 years	0,002895	0,000579	0,001517
6 years in steps of 1 year	0,002526	0,000707	0,001429
7 years in steps of 1 year	0,00235	0,000773	0,001462
8 years in steps of 1 year	0,002179	0,000919	0,001501
9 years in steps of 1 year	0,00262	0,000851	0,001595
10 years in steps of 1 year	0,002515	0,000931	0,001651
15 years in steps of 1 year	0,002027	0,001756	0,001922
Entire period (10 trials)	0,002098	0,001624	0,001904

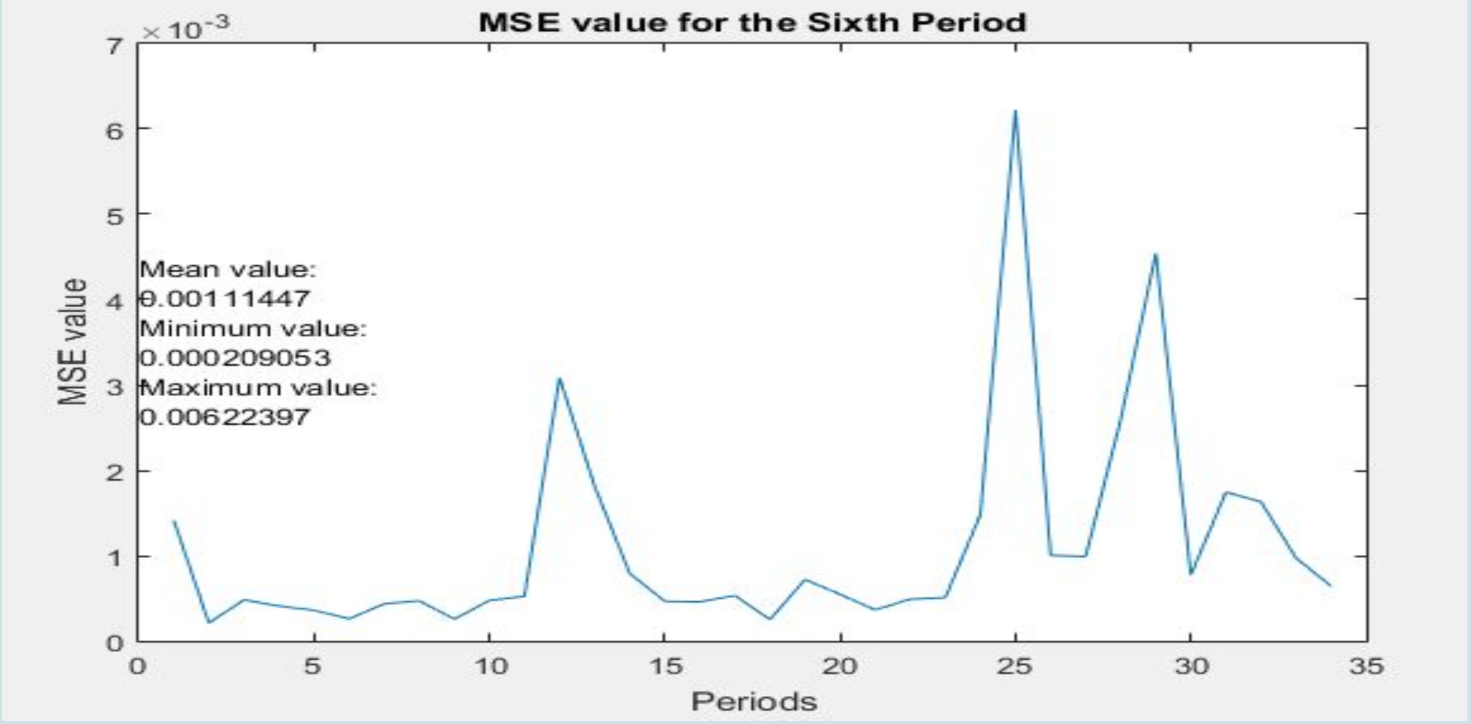
Modeling results concerning the R^2 error value obtained for the Perceptron ANN

The obtained values for the appropriate length of modeling periods			
The length of the quotation period on the PPE DAM	maximum	minimal	mean
month	0,910676	0,13284	0,671464
quarter	0,883035	0,260872	0,664489
half-year	0,847599	0,20746	0,622259
year	0,787481	0,395959	0,60331
2 years	0,74061	0,46056	0,567373
3 years	0,655004	0,492299	0,5669
4 years	0,662723	0,467276	0,545216
5 years	0,560887	0,516093	0,539543
6 years in steps of 1 year	0,654797	0,368147	0,533565
7 years in steps of 1 year	0,638559	0,462133	0,536493
8 years in steps of 1 year	0,641572	0,434553	0,516764
9 years in steps of 1 year	0,577501	0,437375	0,507126
10 years in steps of 1 year	0,537034	0,472314	0,501819
15 years in steps of 1 year	0,484907	0,442602	0,45778
Entire period (10 trials)	0,474964	0,411678	0,446714

Selected charts of MSE values for the different periods

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 operation under study	

Selected charts of MSE for the different periods

<table>
<tr><th>The length of the quotation period on the PPE DAM</th><th>MSE error waveforms</th></tr>
<tr><td>Course of MSE errors for half year periods, taking into account the successive number of periods</td><td>
</td></tr>
</table>

Selected charts of coefficient of determination for the different periods

<table>
<tr><th>The length of the quotation period on the PPE DAM</th><th>R^2 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 operation under study</td><td>
</td></tr>
</table>

Selected charts of coefficient of determination for the different periods

The length of the quotation period on the PPE DAM	R^2 error waveforms
Course of R^2 errors for half year periods, taking into account the successive number of periods	

Conclusions and directions for further research

As a result of the research, the impact of the length of data quotations on the Day-Ahead Market (DAM) was proven.

Many detailed research results were obtained, which in particular include the results of the analysis of changes in the MSE index and for R^2 for different length of the training sets, and these indicators points better results for **shorter intervals**.

MSE for the chosen periods:

month: error value from 0.0245483 to 2.489 * 10^{-12},
year: error value from 0.0550218 to 0.000326423,
10 years: error value from 0.00209772 to 0.00162369,

Determination index R^2 for the chosen periods:

month: the R^2 value was in the range 0.13284 to 0.910676,
year: the R^2 value was in the range 0.395959 to 0.787481,
10 years: the R^2 value was in the range 0.472314 to 0.537034.

- It was found that optimal period of neural modeling for the Day Ahad Market of Polish Power Exchange two factors should be taken into account.

- Despite of value of the MSE and R^2 error **the stability** understood as the scope of data in a given period should be taken into account.

General remark

Based on the conducted neural modeling for subsequent periods of data recording in the years 2002-2019:

The quality of model measured by both MSE and R^2, obtained for individual time intervals (month, quarter, half-year, year, etc.) shows the similar results (smaller MSE, higher R^2.) for given period.

Regardless the data were from the beginning of the period in 2002, or they are closer to the current times, the value o MSE and R^2 were similar.

It was noted that the differences are visible in the aspect of the length of the training set itself, different results were obtained for the month, quarter, half-year, year, etc., which was tried to be shown in this work.

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Thank You for attentions

Any questions ???