sciendo
Control and Cybernetics
vol. 51 (2022) No. 4
pages: 557-583
DOI: 10.2478/candc-2022-0029

Neural modeling of prices on the Day-Ahead Market at the Polish Power Exchange supported by an evolutionary algorithm and inspired by quantum computing*

by

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Abstract: The purpose of the work, presented in this article, was to obtain a price model for the Day-Ahead Market of the Polish Power Exchange (PPE). The resulting proposed models are based on Artificial Neural Networks (ANN), and the involved suggested improvement concerns the proper selection of both the type of network and the factors used in model construction. The article also proposes a new approach to the ANN with the implemented quantum learning model. The purpose of the research was to analyze factors, which exert influence on the quality of the model, like weather or economic factors, or the type of neural network used. The model determines the relationship between the price and the volume of electricity for a given hour of the day.

The mean square error and the coefficient of determination were used to measure the quality of the obtained models. The results from the experiments performed indicate the possibility of developing improved models of the Day-Ahead Market.

Keywords: Polish Power Exchange, Day Ahead Market, modeling of energy market, quantum inspired neural network

1. Motivation

The main subject of the research here reported was to build a Day-Ahead Market (DAM) model for price prediction using an artificial neural network and to examine the impact of neural network types, as well as the impact from various factors on the quality of the model. The next stage of research was the

*Submitted: October 2022; Accepted: December 2022. The paper is an extended version of the one presented during the BOS/SOR2022 conference in October 2022.

implementation of the DAM model using a quantum-inspired artificial neural network. Such a network constitutes a proposal for a new method of modeling of the DAM system.

Modeling was based on data from the Day-Ahead Market since the beginning of its operation, i.e. the data for the period between the second half of 2002 and June 30, 2019. The work here reported is a continuation of previous research on DAM modeling in Poland, see Ruciński (2017, 2018, 2019, 2022), Tchórzewski and Ruciński (2016, 2018, 2019).

With the deregulation of the electricity market in Poland, involving, in particular the Day-Ahead Market system, operating on the Polish Power Exchange as a subsystem of Polish Power Exchange (POLPX), the phenomenon of competition and changing market conditions has emerged, affecting suppliers, consumers, prosumers and intermediaries in the trading and in supply of electricity. Therefore, there is a need to build appropriate models of the Day-Ahead Market system, which will be able to model the operation of this market, taking into account its nature, including its changes, for the needs of all market participants, i.e. both suppliers and customers, as well as the increasing number of intermediaries, participating in electricity trading, and even the prosumers.

The expected outcome of the research is, first of all, to obtain a correct (neural) model of the Day-Ahead Market (DAM) system and to verify the possibility of improving its quality by using quantum-inspired networks (QiANN) (see Tchórzewski, 2013).

2. Description of the relevant market

The rules for the operation of the PPE system in Poland are set forth in the Energy Law of April 10, 1997, and the related implementing acts. The Energy Law does not provide for specific restrictions on the formation of various energy trading modes. Currently, the Polish energy market system consists of three subsystems (called segments): Contract Market System, Share Market System, and Balancing Market System (see Mielczarski, 2000).

The contract market system is a system of electricity trading, based on bilateral contracts, concluded directly between electricity generators and end-users or electricity trading companies.

The exchange market system is a system of energy trading on the power exchange (PPE) mainly on the DAM (PPE also includes the Intraday Market).

The DAM system consists of 24-hour trading periods, during which Exchange Members can buy and sell electricity. Participants of the Exchange send buy or sell orders for each hour, based on which a supply curve, resulting from the sell orders (see Fig. 1 – the curve marked in red) and a demand curve, based on buy orders (the curve marked in blue), are created.

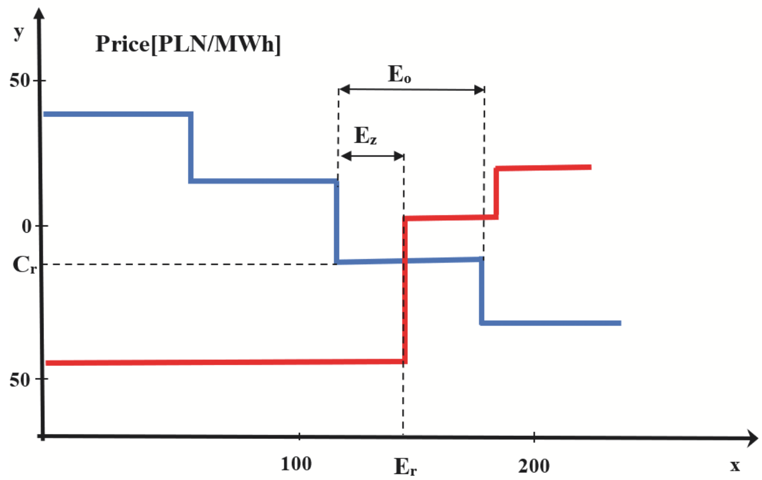

Figure 1. The courses of the supply curve (red) [PLN / MWh] and the demand curve (blue) [PLN / MWh] for the volume of electricity at PPE S.A. intersect (the method of determining the equilibrium price and trading volume for each hour of the day). Symbols: X-axis - electricity volume [MWh], Y-axis - electricity price [PLN / MWh], E_r - ee volume value, for which the supply is equal to the demand and the C_r price is determined (equilibrium price, transaction price), E_z - the volume of energy purchased at the transaction price, E_o - the total volume of energy offered at the transaction price. Source: Mielczarski (2000)

3. Research methodology

For the purpose of modeling of prices in the DAM system, relevant research experiments were developed using the prices and the volume of energy sold in the given periods as a reference. In addition, the influence of weather factors (temperature, sunshine, wind strength, humidity, cloud cover) and economic factors (size of public debt, size of the state budget, rate of inflation, money supply) were also considered. The research plan consisted of the following steps:

Step 1. Implementing the models of the Day-Ahead Market System using data listed on the DAM in MATLAB and Simulink environments.

Step 2. Analysing the obtained models in terms of the impact of the size of the learning sets on model quality, the impact of the selection of various factors (variables) on building of the model, the impact from the type of neural networks used on the quality of the obtained model, etc.

Step 3. Implementing neural models and developing a new proposal of quantum-inspired neural models with a quantum-inspired artificial neural network model based on 12 parallel neural networks*.

Step 4. Comparative analysis of the obtained models.

Step 5. Discussion of the obtained results and formulation of conclusions and directions for further research.

4. The process of selecting factors for building the Day-Ahead System model

4.1. General characteristics of the models identified

Energy markets have been the subject of many studies (see, for instance, Bai and Ng, 2002; Lago et al., 2021), and these studies have generally focused on multivariate models for estimating the number and the selection of the relevant factors. There are also proposals for methodologies meant to estimate the number of factors, using the adopted convergence criteria, in order to do so, involving comprehensive statistical analysis of classification issues and correlations between selected factors.

In order to study the impact of various factors on the quality of the DAM model, five models containing different factor sets were built for analyzing their impact on the quality of the model. The study focused on two main groups of factors, namely economic factors and weather factors. The following factors were taken into account:

1. volume of ee sold in a given hour of the day,
2. temperature,
3. insolation,
4. wind force,
5. humidity
6. cloudiness
7. level of inflation,
8. magnitude of debt,
9. balance of state expenditures,
10. money supply.

*The idea of introducing 12 neural networks is explained in detail in Section 7 of this paper.

The following five models were built for the purposes of this study:

1. one-factor model, i.e., based solely on the volume of ee sold in a given hour of the day,
2. a model containing all factors, in which all normalized data, corresponding to factors from 1 to 10 above, were taken into account.
3. a model containing weather factors, in which factors from 2 to 6 were considered.
4. a model containing economic factors, in which factors from 7 to 10 were considered.
5. a model containing weather factors and economic factors, in which factors from 2 to 6 were taken to create a separate network for average daily energy requirements and then factor 1 and factors from 7 to 10 were considered, as this is shown in Fig. 1.

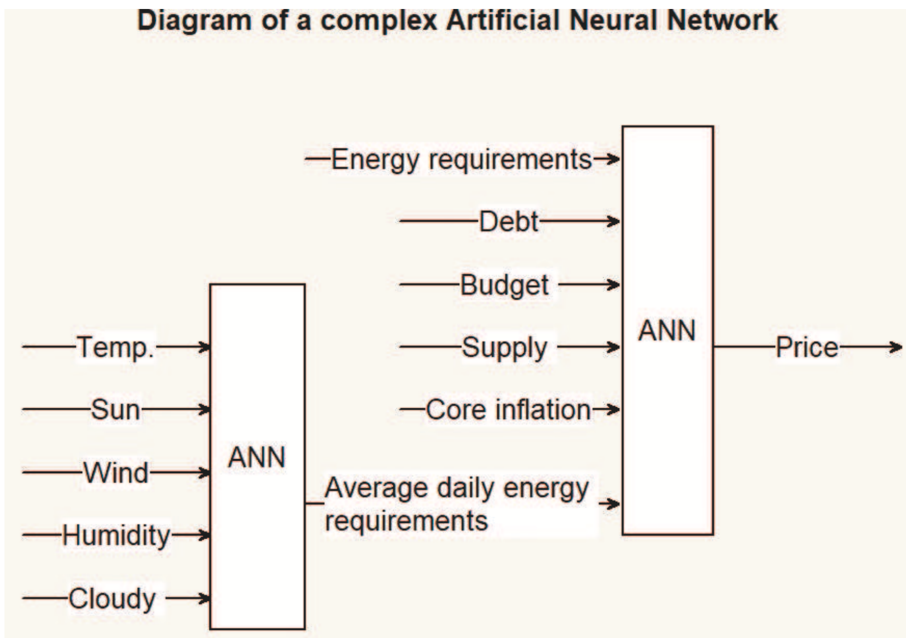

Figure 2. Diagram of the ANN network to which the weather factors enter indirectly. Source: Own study.

Each of the five models was built and tested over the same time interval using the same ANN. The data for the study involved a semiannual data set with different input data sets (models 1 through 5) and the same set of prices as model output. It should be noted that due to fact that different factors were taken into account, they had to be brought to comparable values. In this case, the normalization consisted of a quotient transformation. The reason for this approach was that the data were of different types, including temperatures in degrees Celsius [C] or wind speeds in [km/h], and thus were not comparable with each other. The transformation formula applied is as follows:

$$xn_i = \frac{x_i}{\sum_{i=1}^{p} x_i}, \tag{1}$$

where:

xn_i – i-th normalized value,

x_i – i-th original value,

p - the number of samples.

Each of the five adopted models was trained twenty times. The selected results describing model quality (assessed with MSE and R^2) are presented in Tables 1 and 2 and in Figs. 3 and 4.

4.2. Model selection

Models taking into account only economic and weather factors (i.e. models 3 and 4), when assessed by the adopted criteria showed that their quality is weaker than that of the other ones: MSE equal from 5.51E-05 to 4.95E-05, and R^2 equal from 0.496689 to 0.560401.

The quality of the other three models turned out to be quite similar. Also interesting from the implementation point of view are the results of the first model, based only on the volume of ee sold in a given hour of the day, whose results are comparable to those of model no. 2, containing all factors, and of model no. 5, containing selected factors. In this case, the simplest model based only on the volume of ee sold in a given hour of the day, which is a direct derivative of electricity demand, correctly represents the operation of the system. In the opinion of the present author, the similarity of the results of these models (1, 2 and 5) results from the fact that the impact of economic and weather factors is already taken into account in the magnitude of energy demand.

5. Analysis of selection of artificial neural networks

Another issue, which was studied, was the effect of selection among the artificial neural network models, i.e. Perceptron ANN, Radial ANN and Recursive ANN, on the quality of the obtained neural model of the Day-Ahead Market

Table 1. Examples of MSE results for individual models with different sets of factors. Rows show MSE exemplary values for the given training. Source: Own study.

Model no.	Sequential training number						
	First	Second	Third	Fourth	Fifth	Sixth	Seventh
1	2.52E-05	3.12E-05	2.49E-05	2.70E-05	2.26E-05	2.55E-05	2.96E-05
2	2.33E-05	2.20E-05	2.38E-05	2.00E-05	2.06E-05	2.26E-05	2.09E-05
3	5.51E-05	5.31E-05	5.40E-05	5.27E-05	5.26E-05	5.30E-05	5.38E-05
4	4.95E-05	4.84E-05	4.63E-05	4.74E-05	5.04E-05	4.96E-05	5.42E-05
5	2.62E-05	1.58E-05	2.06E-05	2.17E-05	2.24E-05	2.46E-05	2.01E-05

Table 2. Examples of results regarding the coefficient of determination R^2 for various models. Source: Own study

Model no.	Sequential training number						
	First	Second	Third	Fourth	Fifth	Sixth	Seventh
1	0.8006	0.882303	0.842319	0.835333	0.83776	0.809407	0.846567
2	0.833067	0.829533	0.82373	0.8546	0.846465	0.840213	0.84505
3	0.469712	0.496689	0.485287	0.503741	0.504631	0.500658	0.486556
4	0.544816	0.560401	0.586853	0.571416	0.534766	0.546944	0.4941
5	0.80445	0.756447	0.805817	0.789157	0.824628	0.799346	0.770874

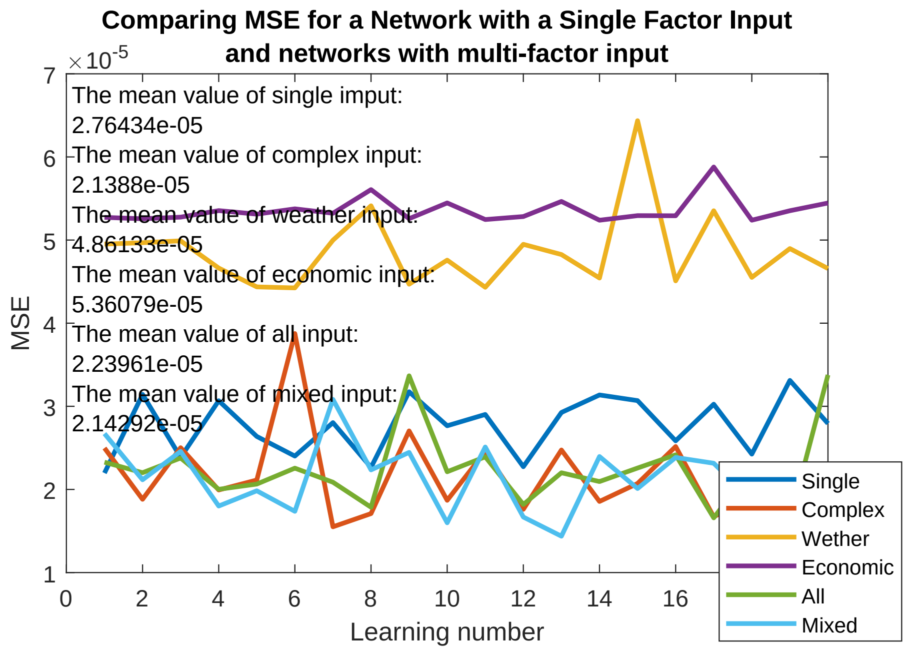

Figure 3. Comparison of the courses of values of the MSE error for the models tested in the study reported. Symbols: x-axis – the ordinal value of subsequent model training attempts, y-axis - MSE value for a given sample. Source: Own elaboration in the MATLAB and Simulink environment.

system. Many studies analyze information processing networks, among them, for instance, Osowski (2020) or Catalão et al. (2022). It was assumed that the main purpose is to study the quality of modeling performed with the different types of ANN. There are works in the literature (see Conejo et al., 2005; Ziel and Weron, 2018) that present the studies of the DAM system models meant for electricity price forecasting, including the ARIMA autoregressive moving average model (see Bissing et al., 2019). The research results also take into account various aspects, such as hourly price series, power demand, etc.

The selected models have been implemented and tested for different periods of operation of the DAM system in TGE S.A., namely the periods from a single month, through a quarter of a year, half a year, three quarters, a year, 2 years, ..., up to 15 years, and then also for the entire already indicated time period of operation of PPE S.A. (2002-2019). The research was carried out in MATLAB and Simulink environments using proprietary m-files and DLT. The coefficient

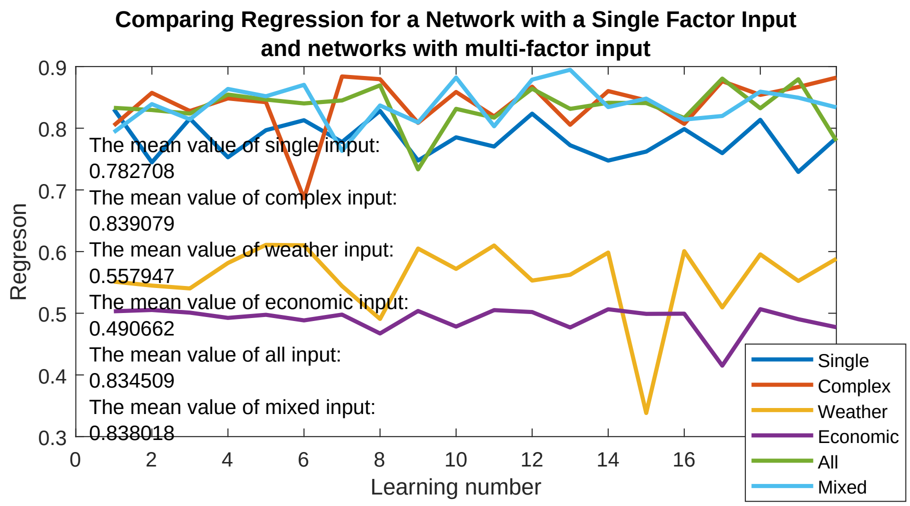

Figure 4. Comparison of the courses of values of the coefficient of determination R^2 for models containing different sets of factors. Symbols: x-axis - ordinal value for subsequent ANN training attempts, y-axis - R^2 value for a given sample. Source: Own study in the MATLAB and Simulink environment (see Mrozek and Mrozek, 2010)

of determination R^2 and the mean squared error MSE were used again as the yardsticks of model quality.

As a result of the investigations carried out, it turned out that the Perceptron ANN is relatively the best neural model for the DAM system, although the MSE error and determination coefficient values are close to those obtained for the Recursive ANN. During the six-month period adopted for further research (see Ruciński, 2022), the MSE error for the Perceptron network ranged from 0.006723 to 0.001065. The MSE error for the Recursive network, which ranged from 0.006723 to 0.00025243, was also relatively good, although slightly worse than that for Perceptron.

For each period and for each type of network, a series of trainings were carried out. As a result, models were obtained whose quality was again described by two parameters, MSE and R^2. In order to standardize the evaluation criterion, an aggregate measure taking into account both criteria was introduced, which can be described as follows:

$$O = \sum_{i=1}^{n} w_i o_i \tag{2}$$

Table 3. Characteristics of artificial neural networks used in research experiments. Source: Own elaboration in MATLAB and Simulink environment using m-files and DLT.

Parameter	Perceptron Network	Recursive Network	Radial Network
number of layers	2	2	2
number of neurons in the hidden layer	24	24	depends on the number of input vectors, from 30 to 6221
number of neurons in the output layer	24	24	24
first layer transformation function	tansig()	tansig()	radbas()
second layer transformation function	purelin()	purelin()	purelin()
evaluation function	MSE, R^2	MSE, R^2	MSE, R^2

where:

n – number of sub-criteria;

o_i – i-th sub-criterion value;

w_i – i-th weight of the sub-criterion,

where, in turn:

$$\sum_{i=1}^{n} w_i = 1. \tag{3}$$

The mean values of MSE and R^2 were adopted as the criteria for network assessment. In this case, the weights of both factors were equal and amounted to 0.5 and n is, of course, equal 2. In addition to the aggregate measure of network quality, a measure of stability for a given time interval was introduced, referred to further on as the dispersion function, understood as the difference between the extreme values of the so-called dispersion (the difference of maximum and minimum values of MSE and R^2).

$$r\,(o) = \sum_{i=1}^{n} w_i (o^i_{max} - o^i_{min}), \tag{4}$$

where:

$r\,(o)$ – dispersion function,

o^i_{max} – i-th maximum value of a given criterion,

o^i_{min} – i-th value of a given criterion.

The dispersion function describes the stability of a given network over a given period of time. Figure 4 shows that for a shorter period, e.g. a month or a quarter, the dispersion is greater, and for a longer period it is smaller. Therefore, this factor should be taken into account during the selection of the data range for building models. It is also worth noticing that the dispersion measure is basically independent of the network type.

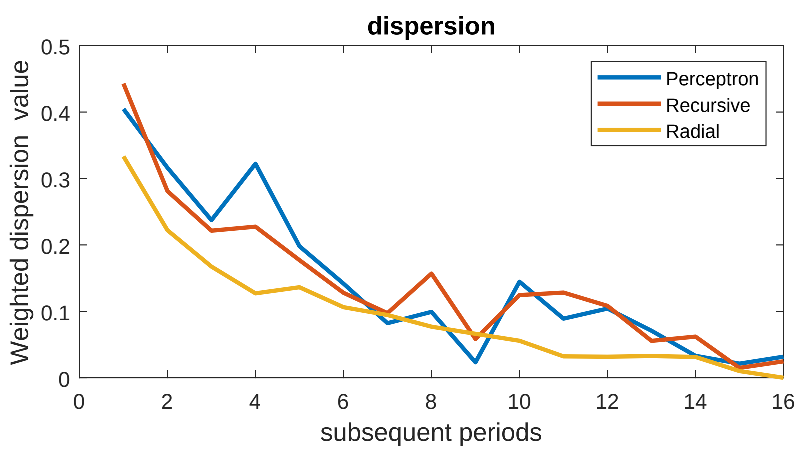

Figure 5. Values of the dispersion function for individual networks in successive periods. Source: Own study.

6. Analysis of the influence of the length of the learning data period on the predictive abilities of models

The main purpose of this stage of research was to determine an acceptable time horizon of prediction for given learning period that can be used for prediction based on the known ANN neural models of the DAM. system. The analysis was conducted using data covering the period of operation of PPE S.A. from 2002 to 2019 (the first half of the year). The value of R^2 was used as a criterion for evaluating the ability of individual models to predict the volume-weighted average electricity prices.

Examination of prediction quality for each period of time, taken as the learning period, proceeded in the following way:

1. Train the ANN network of the Day-Ahead Market system for a given length of the learning time period, i.e., month, quarter, half-year, ..., 5 years (see Table 4 – “ANN learning period length”).
2. Take the trained ANN network and perform simulation with the values shifted by “Prediction shift in days” as the data set (see Table 4 and Fig. 6).
3. Calculate the regression indicator R^2 and store it.
4. Move the prediction frame by “Prediction shift in days” for a given period (e.g. for a month shift = shift +2).
5. If the number of cycles[†] for a given period did not exceed the “Number of cycles” value (see Table 4) - return to point 2.
6. If the number of cycles for a given period reached the value of “Number of cycles”, end the procedure.

The scheme for the study of the prediction quality for a given period (in this case, one month) for the ANN model is shown in Fig. 6. As shown, the prediction based on the trained ANN and starting from the dataset described in ”Prediction shift in days”, after calculating the prediction quality (regression indicator R^2), the period is shifted forward by the value specified in the ”Forecast shift in days” parameter and prediction quality is calculated. The procedure is repeated 10 times (parameter described in the ”Number of cycles”).

The study of predictive capabilities consisted in estimating the forecast for a given ANN (see Table 5 – “ANN learning period length”) by increasing the forecast period by a specified value (see Table 5 – “Prediction shift in days”)

The values of the regression index for the successively increased prognostic periods for a given research period are provided in Table 5, see “Mean Regression Value for a given cycle”. The notion of a “cycle” is illustrated in the scheme of Fig. 6.

Predictive abilities were assessed for the selected neural models of the DAM system, assuming the following ranges of values as the classification criteria for the regression index (see Nazarko, 2018):

1. “ideal” forecast: 0.90–1.00,

[†]the number of cycles indicates how many times the period is moved forward; in this case it is 10 times.

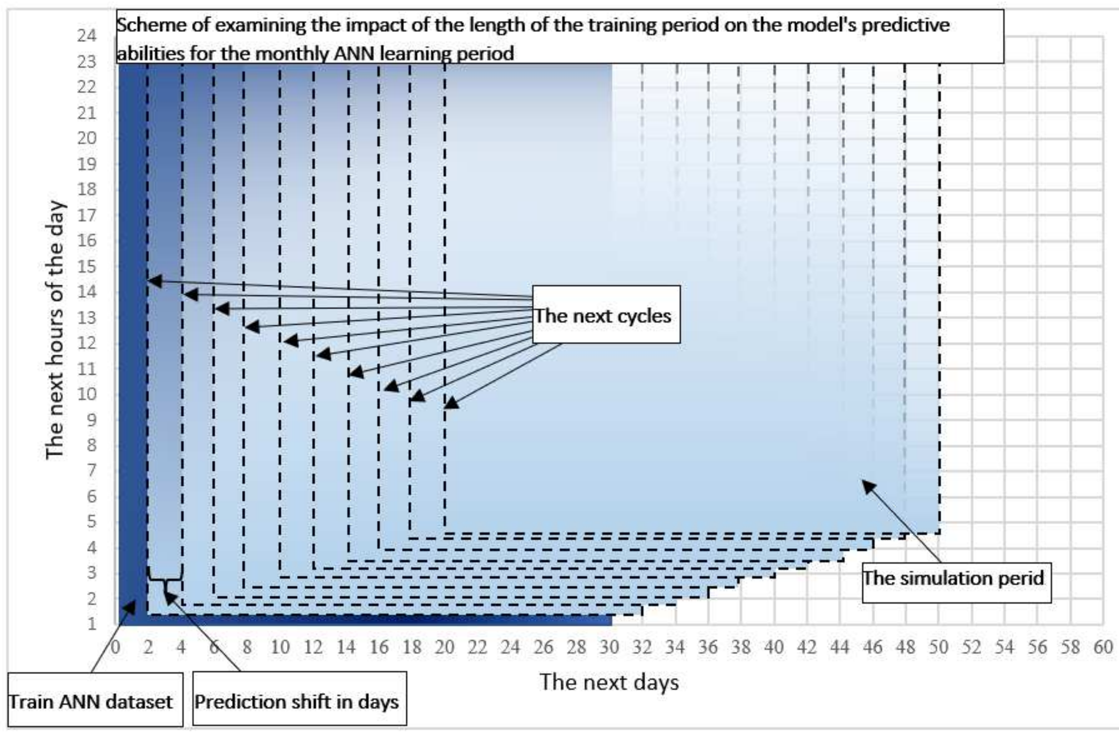

Figure 6. An example of examining the impact of the training period on the predictive abilities of the model for one month. Source: Own study.

Table 4. Assumptions adopted for the ANN model quality analysis for individual data sets. Source: Own study.

ANN learning period length	Prediction shift in days	Number of cycles
Month	2	10
Quarter	7	10
Half-year	12	10
1 year	24	10
2 years	48	10
3 years	72	10
4 years	96	10
5 years	120	10

Table 5. Numerical values of the index R^2 for the system models for individual data sets and individual prediction periods. Source: Own study

	ANN learning period length							
	Month	Quarter	Half-year	1 year	2 years	3 years	4 years	5 years
	Prediction shift in days							
Mean R^{2*}	0.6573	0.6508	0.6487	0.6490	0.6063	0.5736	0.5607	0.5010
	0.6088	0.6139	0.6170	0.6335	0.5931	0.5622	0.5466	0.4992
	0.5778	0.5959	0.6042	0.6128	0.5809	0.5295	0.5270	0.4889
	0.5482	0.5738	0.5881	0.5993	0.5555	0.5099	0.5183	0.4750
	0.5213	0.5516	0.5575	0.5809	0.5265	0.4968	0.5151	0.4643
	0.4920	0.5237	0.5445	0.5651	0.5180	0.4917	0.5014	0.4477
	0.4626	0.4919	0.5314	0.5443	0.5129	0.4885	0.4871	0.4414
	0.4402	0.4663	0.5123	0.5188	0.5055	0.4869	0.4670	0.4218
	0.4140	0.4475	0.4986	0.4746	0.4968	0.4793	0.4529	0.3935
	0.3929	0.4250	0.4835	0.4620	0.4646	0.4805	0.4302	0.3914

* i.e. Mean R^2 values for consecutive cycles

2. "optimal" forecast: 0.60–0.89,
3. "acceptable" forecast: 0.50–0.59,
4. "unacceptable" forecast: below 0.50.

In the above context, an additional indicator (WsP) was also proposed in order to examine the predictive ability of the DAM system model. The assessment of the predictive ability of the tested models (in days) taking into account this indicator is presented in Table 6.

The predictive ability of the DAM system model in terms of WsP was evaluated from the point of view of its impact, understood as the length of the period recorded in Table 6 according to the following relationship:

$$WsP = \frac{nd}{wm} \tag{5}$$

where:

nd – number of prediction days corresponding to the ranges of the prediction quality classification, provided above ("ideal", "optimal", "acceptable", "unacceptable"),

wm – the number of days used in creating a given model of the DAM system, i.e. the length of the learning period (see Table 6 – "ANN learning period length").

This indicator was introduced as an auxiliary one to better estimate the predictive ability of the model. The main point of introducing this indicator is to determine the predictive ability of the model in relation to the size of the set on which it was taught.

For example, a 6-day prediction horizon for a monthly learning set is not comparable to a 6-day horizon for a yearly set, since in the former case WsP = 6/30 = 0.2, and in the latter case WsP = 6/365 = 0.0164, so it is by an order of magnitude smaller. This may be so, despite the fact that the regression index R^2 itself for the annual set at this horizon might be in the same predictive range, for example, "optimal".

The analysis of the results regarding the predictive power of the models developed, according to the classes of values of the regression index R^2, these results being presented in Table 6, shows that the best WsP coefficients for the "optimal" forecasts occur in semi-annual periods, for which its value is at 0.2. The annual period, compared to other periods, is also characterized by a relatively high value of the WsP coefficient of 0.19. The remaining periods are characterized by worse values of the WSP coefficient for the "optimal" forecast, while there are no positive results for the "ideal" forecast. For the "acceptable" forecast, there is a clear relationship between the size of the ANN model, and the value of the index, which ranges from 0.67 for one month to 0.07 for five years. The values for half a year, one year and two years are the same, at 0.53.

Taking into account the results for the "optimal" and "acceptable" forecasts, it can be admitted that the six-month period should be assumed as the basis for further research on the neural model of the RDN system.

Table 6. Assessment of the predictive abilities of the neural models of the DAM system according to the classes of values of R^2. Source: Own study.

ANN learning period length	perfect forecast [days]	optimal forecast [days]	WsP	Acceptable forecast [days]	WsP	Unacceptable forecast [days]
Month	0	4	0.13	20	0.67	over 20 days
Quarter	0	14	0.16	42	0.47	over 42 days
Half-year	0	36	0.2	96	0.53	over 96 days
Year	0	72	0.19	192	0.53	over 192 days
2 years	0	48	0.07	384	0.53	over 384 days
3 years	0	0	0	288	0.27	over 288 days
Four years	0	0	0	576	0.40	over 576 days
5 years	0	0	0	120	0.07	over 120 days

7. Implementation of quantum inspirations to build the DAM system model based on 12 networks

7.1. Introductory remarks

Quantum calculations and their actual implementation are the subject of many studies, presenting both general rules (see Adamowski, 2019; Bernhardt, 2020; Chudy, 2011; Feynman et al., 2014; Heller, 2016; Hirvensalo, 2004; Sawerwain and Wiśniewska, 2015), as well as specific practical applications, including those related to building prediction models (see Alaminos et al., 2020; Ge and Wenping, 2022; Ciechulski and Osowski, 2014; Wright and Jordanov, 2017, Wiśniewska, Sawerwain and Obuchowicz, 2020). This exemplary short list of publications shows that the quantum inspirations constitute the subject of wide interest and research. The publications show different approaches to the subject; however, it is a dynamically developing field of research.

The proposed approach to modeling with the use of quantum inspirations is based on the fundamental assumptions and achievements of quantum computing. The proposal is based on the assumption that Quantum-Inspired ANN can be implemented as a register of a given order of magnitude describing a mixed quantum state for a given real value. Such a quantum state is created as a result of converting a numerical value stored in the decimal number system into a value stored in the binary system, assuming the accuracy of representing a given decimal number by 12 values in the binary system.

The number so stored is then transformed into a 12-element matrix of quantum mixed states. As a result of this approach, for each value stored in the decimal number system, representing data for the input to the neural network, the values of weights and biases and output data are represented by a 12-column by two rows matrix of quantum mixed states (12x2).

The essence of the new approach is to build a Quantum-Inspired ANN for each qubit of the quantum mixed state, which leads to the necessity of building 12 quasi-parallel ANNs from the youngest cubit to the oldest.

For example, the first ANN consists of the first qubit of the quantum state matrix representing the input values, the first qubit of the quantum state matrix representing the values of the weighting matrix, the first quantum state representing the bias values, and the first qubit of the quantum state matrix representing the output values that are used to train the first ANN.

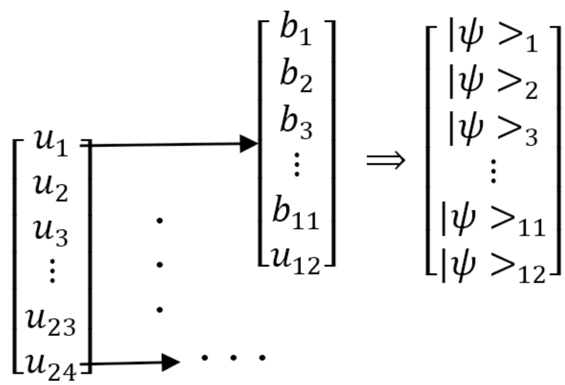

Figure 7. The example of transformation of a real value into quantum mixed states. Symbols: u_n – real value, b_n- binary value, |Ψ>- quantum mixed state. Source: Own study.

The quantum computations carried out involve the occurrence of redundant values at various stages of computation, which are transferred to the higher-order neural network.

After learning the twelve quantum-inspired ANNs built in this way, one obtains a quantum-inspired neural model having as outputs 12 quantum states for

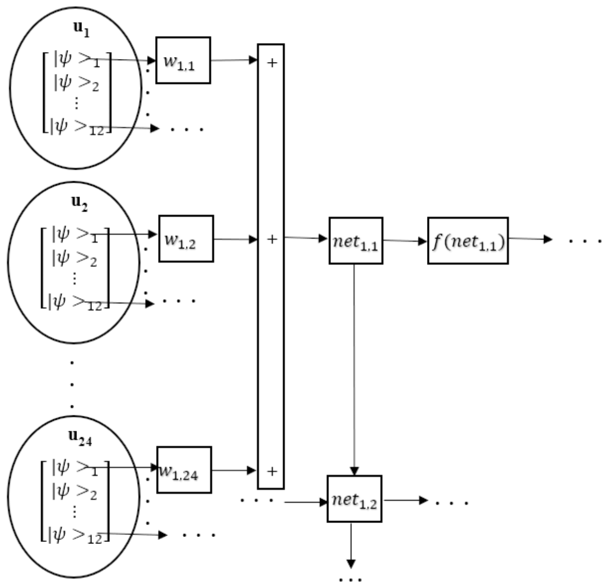

Figure 8. The example of processing of the mixed quantum states for the hidden layer for first qubit into first neuron. Symbols: f(net$_n$)– activation function, net$_n$- adder value, w$_n$- weight density matrix, $|\Psi>$- quantum mixed state. Source: Own study.

each decimal value. Measurement of quantum mixed states allows for obtaining of pure states ket 0 or ket 1. Pure states are treated as binary values, which are then converted to decimals.

The first operation to prepare for the construction of the ANN model based on mathematical structures used for quantum calculations is the conversion of numbers in the decimal system to binary values.

7.2. Binary representation

In the first stage, the input values, i.e., the volume of electricity supplied and sold, and the output values[‡], i.e., the volume-weighted average price of electricity obtained in each hour of the day, were converted into binary values.

As a result of the first stage of data preparation, a binary matrix representing the decimal values for the input and output data is obtained. In the case of

[‡]Considering the one-factor model, i.e. based solely on the volume of ee sold in a given hour of the day (see Section 4 of the paper),

this particular study, it was a 12-element binary vector representing a given real value. Each element of a binary vector represents the corresponding order of magnitude, i.e., the first element represents the largest order of magnitude and the last one – the smallest.

The next stage of the quantum-inspired ANN design was the conversion of binary values into quantum mixed states and density matrices in the Hilbert space. It was assumed that individual binary values represent pure states in this space.

The conversion consists in adding the products of successive powers of two and the corresponding digits of a binary number. In this case, real numbers smaller than zero were subject to conversion. The respective algorithm came down to the following steps:

1. the value of a given real number r is multiplied by 2,
2. if $2r$ is greater than 1, then the value of a binary number for this order of magnitude takes the value 1 and then 1 is subtracted from the value of 2,
3. if $2r$ is smaller than 1 then the value of a binary number for this order of magnitude is 0,
4. if the length of the binary representation of the real number is not sufficient, we return to point 1,
5. if the length of the binary representation of the real number is sufficient, the algorithm terminates.

7.3. Quantum representation

In the quantization process, quantum mixed states were created on the basis of the values of binary numbers, 0 or 1, and they were treated as pure states of the quantum value state vector, i.e. ket 0 and ket 1. The idea of creating a quantum mixed state was based on the use of the property that, as a result of the measurement, the probability of a quantum bit being in the $|1>$ state is $|\alpha|^2$ and, analogously, the probability of a bit being in the $|1>|$ state is $|\beta|^2$. Thus, assuming that $\alpha = \beta$, we can write $2|\alpha|^2 = 1$, from which the positive value (actual state) leads to the determination of the lower limit of the probability modulus value for:

$$\alpha = \beta = \frac{\sqrt{2}}{2} \approx 0.71. \tag{6}$$

Based on the relation (6) it is possible to determine the probability module for pure states, e.g., for pure state 1, the dominant interval of the probability module is in the range $0.71 \leq \alpha \leq 1$, the given value α was drawn from this range, and the corresponding value β was determined from the principle of superposition:

$$\alpha^2 + \beta^2 = 1. \tag{7}$$

The procedure applied for the value of ket 0 was the same.

7.4. Density matrices

When analyzing the construction principle of the quantum ANN model, it can be seen that the weight matrices are linear operators for the input data, which are quantum mixed states, representing the volume of energy. Taking this property into account, the quantum states of the weights were transformed into their density matrices.

Thus, for example, for the weight w_1,1, which has the value in the decimal number system of 0.361760584314686:

1. conversion to binary[§] is: 0.010111001001,
2. conversion to quantum mixed states[¶] (see Table 7),

Table 7. Examples of quantum mixed state values. Source: Own study

Value of the corresponding bit		
Binary	Module α	Module β
0	0.820	0.572
1	0.014	1.000
0	0.900	0.436
1	0.243	0.970
1	0.527	0.850
1	0.704	0.710
0	0.890	0.456
0	0.770	0.638
1	0.510	0.860
0	0.920	0.392
0	0.890	0.456
1	0.475	0.880

3. conversion for the first qubit from Table 7 into the density matrix is done as follows:

[§] using the algorithm from the section devoted to binary representation, 7.2.
[¶] using the algorithm from the section devoted to quantum representation, 7.3.

$$|\psi><\psi| = \begin{bmatrix} 0,820 \\ 0,572 \end{bmatrix} \begin{bmatrix} 0,820 & 0,572 \end{bmatrix} = \begin{bmatrix} 0,820^2 & 0,820 \cdot 0,572 \\ 0,572 \cdot 0,820 & 0,572^2 \end{bmatrix} = \begin{bmatrix} 0,6724 & 0,4690 \\ 0,4690 & 0,3272 \end{bmatrix} \tag{8}$$

The data transformed in this way form the basis for modeling with the Quantum Inspired Artificial Neural Network.

7.5. Findings

Examples are provided below of the results obtained for normalized real data. The results obtained from the Perceptron Artificial Neural Network are presented in Table 8. Then, the sample of results, obtained from the quantum-inspired Artificial Neural Network is presented in Table 9.

The course of the average values for a given day in the entire period under consideration, i.e., 181 days, is shown in Fig. 9.

Table 8. Sample data for three days (01-03.01.2019) obtained from Perceptron ANN. Source: Own study

Hours of the day	Day number						
	1	2	3	Hours of the day	1	2	3
1	0.432	0.327	0.408	**13**	0.442	0.310	0.484
2	0.397	0.305	0.384	**14**	0.433	0.312	0.487
3	0.391	0.285	0.367	**15**	0.457	0.344	0.508
4	0.401	0.291	0.373	**16**	0.463	0.361	0.513
5	0.423	0.316	0.396	**17**	0.424	0.371	0.531
6	0.443	0.311	0.444	**18**	0.418	0.364	0.535
7	0.446	0.324	0.490	**19**	0.418	0.386	0.540
8	0.470	0.382	0.504	**20**	0.439	0.409	0.536
9	0.478	0.339	0.484	**21**	0.475	0.408	0.526
10	0.488	0.328	0.476	**22**	0.493	0.478	0.520
11	0.470	0.332	0.477	**23**	0.442	0.429	0.534
12	0.450	0.320	0.477	**24**	0.478	0.447	0.524

When analyzing the obtained results, we can conclude that it is possible to implement a quantum-inspired Artificial Neuron Network to obtain a model of the Day-Ahead Market System on the Polish Power Exchange. Regarding these results, it can be seen that QiANN shows a greater tendency to average

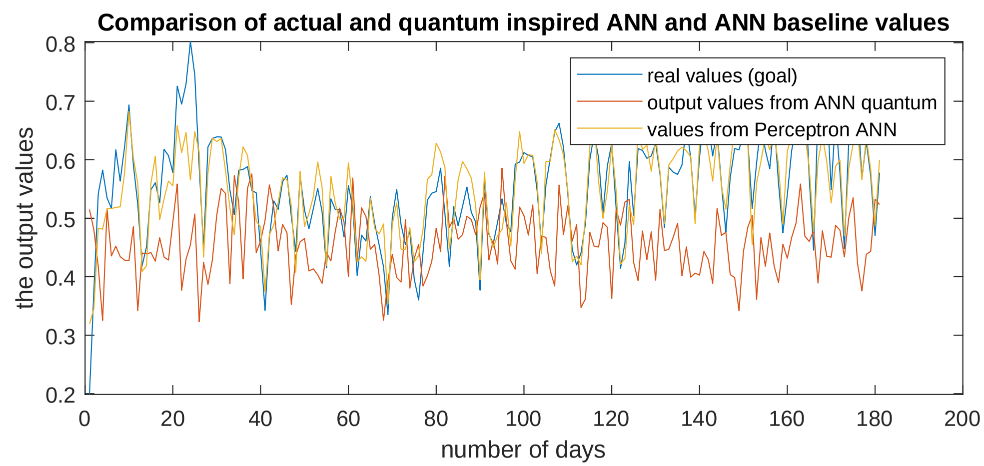

Figure 9. Comparison of the actual normalized values of the price course with the Perceptron ANN model and the quantum-inspired model. Symbols: x-axis (Days number) - consecutive days of the examined period (in this case 181 days), y-axis (the output values from the models and the real) - average normalized value of price. Blue – real normalized price values, yellow – Perceptron ANN output, red – quantum inspired ANN output. Source own elaboration in the MATLAB environment.

Table 9. Results obtained from the Quantum Inspired Artificial Neural Network for three days (01-03.01.2019). Source: Own study

Hours of the day	Day number						
	1	2	3	Hours of the day	1	2	3
1	0.542	0.898	0.724	**13**	0.913	0.048	0.788
2	0.348	0.045	0.176	**14**	0.006	0.036	0.159
3	0.060	0.142	0.713	**15**	0.220	0.114	0.254
4	0.466	0.488	0.137	**16**	0.147	0.179	0.061
5	0.450	0.134	0.389	**17**	0.556	0.614	0.246
6	0.676	0.673	0.384	**18**	0.060	0.841	0.281
7	0.302	0.927	0.427	**19**	0.254	0.523	0.299
8	0.432	0.404	0.638	**20**	0.806	0.461	0.314
9	0.588	0.317	0.003	**21**	0.647	0.266	0.127
10	0.113	0.634	0.635	**22**	0.194	0.942	0.171
11	0.107	0.608	0.576	**23**	0.334	0.528	0.535
12	0.103	0.348	0.689	**24**	0.421	0.868	0.402

the output, i.e., it is more resistant to interference. Notwithstanding this, the average value of the MSE error is definitely higher for it than for the Perceptron Artificial Neural Network. For QiANN it was 0.09, and for Perceptron ANN it was 0.03.

8. Conclusions and directions for further research.

The proposal to improve the quality of ANN-based models through the proper selection of both the type of network and the factors for its construction turned out to be sensible both technically and substantively. The proposed new approach to ANN with the implemented quantum learning model for the Day-Ahead Market of the Polish Power Exchange showed also that building a quantum-inspired model is feasible.

The results for the "classic" Perceptron ANN model compared to the quantum-inspired model indicate the need for further research work on the quantum-inspired model in order to improve it.

References

Adamowski, J. (2019) *Podstawy obliczeń kwantowych* [*Foundations of quan-*

tum calculations; in Polish]. *Lectures at the Faculty of Physics and Applied Informatics*, AGH University, Kraków, http://www.ftj.agh.edu.pl (access: 14.08.2019)

Alaminos, D., Esteban, I. et al. (2020) Quantum Neural Networks for Forecasting Inflation Dynamics. *Journal of Scientific & Industrial Research*, **79**, 2, doi: 10.56042/jsir.v79i2.68439 (access: 12.12.2022)

Bai, J. and Ng, S. (2002) Determining the Number of Factors in Approximate Factor Models. *Econometrica*, **70**, 1, 191–221.

Bernhardt, C. (2020) *Obliczenia kwantowe dla każdego* [*Quantum calculus for everyone*; in Polish]. PWN, Warszawa.

Bissing, D., Klein, M. T. et al. (2019) A Hybrid Regression Model for Day-Ahead Energy Price Forecasting. *IEEE Access*, **7**, 36833-36842.

Catalão, J., Mariano S. et al. (2022) An Artificial Neural Network Approach for Day-Ahead Electricity Prices Forecasting. *Proceedings of the 6th WSEAS Int. Conf. on Neural Networks*, Lisbon, Portugal, June 16-18, 2022; 80-83.

Chudy, M. (2011) *Wprowadzenie do informatyki kwantowej* [*Introduction into Quantum Informatics*; in Polish]. OW EXIT, Warszawa.

Ciechulski, T. and Osowski S. (2014) Badanie jakości predykcji obciążeń elektroenergetycznych za pomocą sieci neuronowych SVM, RBF i MLP [Analysing the quality of prediction of electric energy load with neural networks SVM, RBF and MLP; in Polish]. *Przegląd Elektrotechniczny*, **90**, 8, 148-151.

Conejo, A. J., Plazas M. A. et al. (2005) Day-ahead electricity price forecasting using the wavelet transform and ARIMA models. *IEEE Transactions on Power Systems*, **20**, 2, 1035-1042.

Feynman, R. P., Leughton, R. B. and Sands M. (2014) *Feynmana wykłady z fizyki* [*Feynman's lectures in physics*; in Polish]. Volume 3. *Mechanika kwantowa* [*Quantum mechanics*]. PWN, Warszawa.

Ge, L. and Wenping, M. (2022) A quantum artificial neural network for stock closing price prediction. *Information Sciences*, **598**, 75-85, doi.org/10.1016/j.ins.2022.03.064 (access: 10.12.2022)

Heller, M. (2016) *Elementy mechaniki kwantowej dla filozofów* [*Elements of quantum mechanics for philosophers*; in Polish]. Copernicus Center Press, Kraków.

Hirvensalo, M. (2004) *Algorytmy kwantowe* [*Quantum algorithms*; in Polish]. WSiP, Warszawa.

Lago, J., Marcjasz, G., De Schutter, B. and Weron R. (2021) Forecasting Day-ahead electricity prices: A review of state-of-the-art algorithms, best practices and an open-access benchmark. *Applied Energy*, 293.

Mrozek, B. and Mrozek, Z. (2010) *Matlab i Simulink: poradnik użytkownika* [*Matlab and Simulink: user's guide*; in Polish]. Helion, Gliwice.

Mielczarski, W. (2000) *Rynki energii elektrycznej. Wybrane aspekty techniczne i ekonomiczne* [*Electric energy markets. Selected technical and economic aspects*; in Polish]. ARE S.A. i Energoprojekt-Consulting S.A., Warszawa.

Nazarko, J. (2018) *Prognozowanie w zarządzaniu przedsiębiorstwem. Część IV. Prognozowanie na podstawie modeli trendu* [*Forecasting in enterprise management. Part IV. Forecasting on the basis of trend models*; in Polish]. Politechnika Białostocka, Białystok.

Osowski, S. (2020) *Sztuczne sieci neuronowe do przetwarzania informacji* [*Artificial neural networks for information processing*; in Polish]. OW PW, Warszawa.

Ruciński, D. (2018) Modelowanie neuronalne cen na Towarowej Giełdzie Energii Elektrycznej wspomagane algorytmem ewolucyjnym oraz inspirowane obliczeniami kwantowymi [Neural modeling of prices on Electric Power Exchange supported with evolutionary algorithm and inspired by quantum calculations; in Polish]. Doctoral dissertation elaborated under the guidance of Professor Jerzy Tchórzewski, UPH in Siedlce, IBS PAN, Warszawa.

Ruciński, D. (2019) 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*, 1-2(23), 77-93.

Ruciński, D. (2022) 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. *Studia Informatica. Systems and Information Technology*, 1(26)/2022, 5-24.

Sawerwain, M. and Wiśniewska, J. (2015) *Informatyka kwantowa. Wybrane obwody i algorytmy* [*Quantum informatics. Selected circuits and algorithms*; in Polish]. PWN, Warszawa.

Tchórzewski, J. (2013) *Rozwój systemu elektroenergetycznego w ujęciu teorii sterowania i systemów* [*Development of the electric power system in the perspective of control and systems theory*; in Polish]. OW PWr., Wrocław.

Tchórzewski, J. (2021) *Metody sztucznej inteligencji i informatyki kwantowej w ujęciu teorii sterowania i systemów* [*Methods of artificial intelligence and quantum mechanics in the light of control and systems theory*; in Polish]. Wydawnictwo Naukowe UPH w Siedlcach.

Tchórzewski, J. and Ruciński, D. (2016) Quantum inspired evolutionary algorithm to improve parameters of neural models on example of Polish electricity power exchange. *Electric Power Networks (EPNet)*, 1-8, doi: 10.1109/EPNET.2016.7999349.

Tchórzewski, J. and Ruciński, D. (2018) Quantum-inspired Artificial Neural Networks and Evolutionary Algorithms Methods Applied to Modeling of the Polish Electric Power Exchange Using the Day-ahead Market Data. *Information Systems in Management*, **7**, 3, 201–212.

Tchórzewski, J. and Ruciński, D. (2019) Evolutionarily-Supported and Quantum-Inspired Neural Modeling Applied to the Polish Electric Power Exchange. *Progress in Applied Electrical Engineering (PAEE)*, 1-8, doi: 10.1109/PAEE.2019.8788987.

Wiśniewska, J., Sawerwain, M. and Obuchowicz, A. (2020) Basic quantum circuits for classification and approximation tasks. *International Journal of Applied Mathematics and Computer Science*, **30**(4), 733–744.

Wright, J. and Jordanov, I. (2017), Quantum inspired evolutionary algorithms with improved rotation gates for real-coded synthetic and real world optimization problems. *Integrated Computer-Aided Engineering*, **24**, 3, 203-223.

Ziel, F. and Weron, R. (2018) Day-ahead electricity price forecasting with high-dimensional structures: Univariate vs. multivariate modeling frameworks. *Energy Economics*, Elsevier, 70(C), 396-420.