QUANTUM-INSPIRED ARTIFICIL NEURAL NETWORKS AND EVOLUTIONARY ALGORITHMS METHODS APPLIED TO MODELING OF THE POLISH ELECTRIC POWER EXCHANGE USING THE DAY-AHEAD MARKET DATA

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The paper presents selected results of research on the use of artificial intelligence methods, which are inspired by quantum computing solutions for modelling of electric power exchange systems. Methods used in the modelling of quantum data acquisition, quantization and dequantization of information as well as the methods of performing quantum computations were emphasized. Furthermore, we have analysed the results obtained for the neural model and for the evolutionary algorithm inspired by the quantum computer science. Eventually, the model was verified on the example of the neural model of the Electric Power Exchange (EPE).

Keywords: Artificial Intelligence Methods, MATLAB and Simulink Environment, Modeling of Business Intelligence Process, Quantum Inspired Method, Smart Electric Power System, Electric Power Exchange System

1. Introduction

Due to the rapid development of nanotechnologies and the power system technologies, flexibility towards its operation in terms of the smart electric power system, including smart electric power grid, the demand for new modelling methods is rising. It requires increasing accuracy and robustness (as a specific balance between efficiency and effectiveness).

At the same time artificial intelligence methods used in power system control are rapidly growing. They are frequently used in smart metering, modelling of on-line power transactions, in the development of micro-networks, and in numerous other areas of power engineering with respect to the various subsystems of the power system seen as a technical system, as well as broader - viewed as a technical-economic system [7, 14, 17, 21-25, 29].

Therefore there exists natural need to meet at least some of the demand for new methods and tools for modelling of systems through the use of artificial intelligence methods supplemented with quantum computer solutions. Obviously, that development is connected with the modernization of the existing power system through robust mutual matching of all elements, and not only as their optimization, but seen as methods insufficiently effective and efficient in this area of research [1, 3-6, 9, 12, 15-19, 21-25].

Since 2010 the European Commission developed its own standards, which were set up by a Group of Specialists with a well-defined work schedule for 2010-2020. In Poland those kind of topics are also being carefully researched, among others between 2013-2014, the Energa-Operator carried out an informational and educational project "Neonawyki-intelligent power grids", aimed at promoting development of the Intelligent Power Grids in Poland, and it is currently implemented as a pilot project on Intelligent Helium Network called "Intelligent Peninsula".

It is assumed, for example, networks that use ICT to reduce the costs and increase efficiency, and integrate distributed sources of electricity, including renewable energy. Therefore, the smart grid concept requires interdisciplinary research and application of modern technologies solutions to make system models more flexible, which requires a combined view of power engineering processes with ICT processes [21-27], by using quantum computing solutions.

2. Methods of artificial intelligence inspired by quantum computing solutions

The methods of artificial intelligence susceptible to the methods of quantum computer science include: Artificial Neural Networks (ANN), Evolutionary Algorithms (EA), immunological systems (IMS) and cluster analysis methods (CA), etc. [6, 10, 13, 18, 20, 28]. There have been already many successful attempts inspired by artificial intelligence methods in quantum computer science, especially in order to obtain quantum - inspired artificial neural networks and quantum - inspired evolution algorithms, to which a limited overview of the applied solutions is presented in the available literature [6, 9-10, 12-19 , 21-26].

A specific artificial intelligence algorithm is then adopted and the method of its quantum recording is selected, followed by the quantization of numerical values, calculations on quantum mixed numbers, and after the solution is obtained, its quantization into decimal numbers. The evolution of evolutionary methods by

means of quantum computing is related, among others, to using the possibilities of quasi - parallelization of calculations introduced by quantum computers. In order to implement the methods used in quantum computing, real data has been transformed into binary and quantum ones. The proposed method of quantizing and dequantizing real numbers into quantum numbers [21-25] use the principle of superposition, which for the qubit has the form:

$$(\alpha)^2 + (\beta)^2 = 1,$$ (1)

which for the multi-qubits circuits (for qudids) brings the problem to determining the mixed numbers to the superposition of components:

$$\sum_{i=1}^{n} \varphi_i^2 = 1.$$ (2)

Assuming that in the expression (1) $\alpha = \beta$, it is possible to define the boundary of the probability modules of the pure state of ket 0 and the pure state of ket 1.
This means that two states can be used to obtain the states of mixed value: first by drawing from the dominating range (numbers in the range $<0.71 \div 1>$) ket 0 or ket 1 respectively and the second method by drawing from recessive intervals (numbers in the range $<0 \div 0.71>$) ket 1 or ket 0. In the literature, the Hadamard (H) gate is most commonly used for quantizing mixed numbers, as a singleton quantum gate representing by a 2-dimensional unitary matrix, which is an alternative proposition of quantization given in [18, 23-25]:

$$H = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} = \begin{bmatrix} \dfrac{1}{\sqrt{2}} & \dfrac{1}{\sqrt{2}} \\ \dfrac{1}{\sqrt{2}} & -\dfrac{1}{\sqrt{2}} \end{bmatrix},$$ (3)

where the vectors H | 0> and H | 1> are the basis in the space of states of one cubic Hadamard's base.

The Hadamard gateway function for base vectors | 1> and |0> can be represented as follows:

$$H|0\rangle = \frac{1}{\sqrt{2}}(|0\rangle + |1\rangle)$$

and (4)

$$H|1\rangle = \frac{1}{\sqrt{2}}(|0\rangle - |1\rangle).$$

2.1. Quantum-Inspired Artificial Neural Networks

In the case of ANN inspired by quantum computer science, the first important step was to quantify the weighted sums of individual output neurons in successive layers $net_i^j(t)$, it means that the sum of the product of the vector values of the weights and the vector values of the input quantities are stored in quantum, for example, if i = 1 in the hidden layer j = 1 [13, 16-17, 20-25]:

$$u_1 = \begin{bmatrix} 0.87 & 1 & 0.77 & 0.98 & 0.67 & 0.74 & 0.89 & 0.85 & 0.14 & 0.37 & 0.77 & 0.44 \\ 0.49 & 0 & 0.64 & 0.20 & 0.74 & 0.67 & 0.46 & 0.53 & 0.99 & 0.93 & 0.64 & 0.90 \end{bmatrix},$$

$$w_{1,1} = \begin{bmatrix} 0 & 1 & 0 & 0 & 1 & 0 & 0.51 & 0.49 & 0.52 & 0.40 & 0.38 & 0.49 \\ 1 & 0 & 1 & 1 & 0 & 1 & 0.49 & 0.51 & 0.48 & 0.60 & 0.62 & 0.51 \end{bmatrix}.$$

(5)

so:
$$net_1^1(u_1) = w_{11}^1 \cdot u_1^T = \begin{bmatrix} net_{11}^1 & net_{12}^1 \\ net_{21}^1 & net_{22}^1 \end{bmatrix},$$

which ties different probabilities of modules of their main value in the case of net_1^1 on the diagonal and have mixed values in left elements of matrix. Such obtained value of products (net_1^1) from each of neurons is an activation function argument that creates hyperbolic tangent sigmoid transfer function tansig():

$$y_1^1(t) = f(net_1^1) = \frac{2}{1 + e^{-2\begin{bmatrix} net_{11}^1 & net_{12}^1 \\ net_{21}^1 & net_{22}^1 \end{bmatrix}}} - 1.$$

(6)

In order to determine the value of the activation function quantum matrix net_1^1, dequantization operation was performed.

In this case, an innovative solution using perceptron of ANN was proposed in which as input to the neural network the quantum mixed numbers described in the above square matrix expressing the quasi-mixed probability modules of pure states are implemented, and the real value as the output, the values obtained from the ANN (value net_i^j) [21-25].

Selected results of comparative studies between the quantum neural network adder net_i for the first neuronal output layer for the first input and analogue values of the perceptron adder of the ANN are shown in Figure 1. Selected results of comparative studies between the quantum neural network adder net_i for the second neuronal output layer for the nine input and analogue values of the perceptron adder of the ANN are shown in Figure 2.
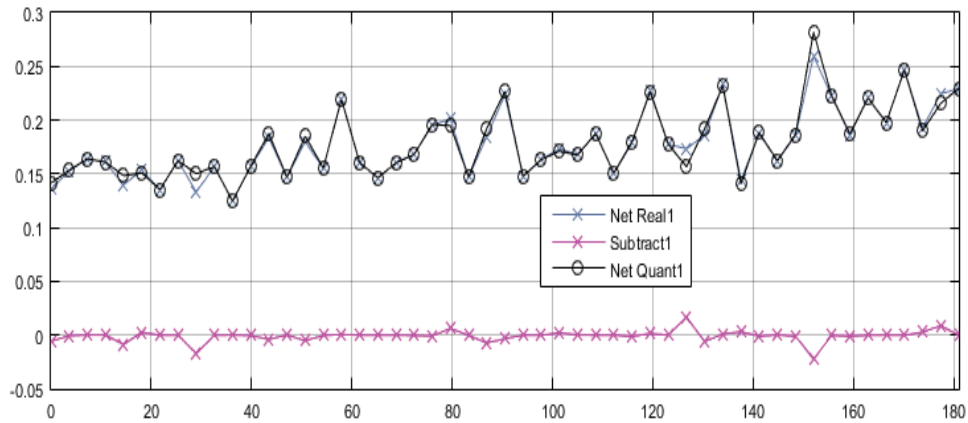
Figure 1. Selected results of comparative studies between the quantum neural network adder net_i for the first neuronal output layer for the first input and analogue values of the perceptron adder of the ANN. *Source*: Own study in MATLAB and Simulink Environment [Embedded MATLAB™, 2002-2016]
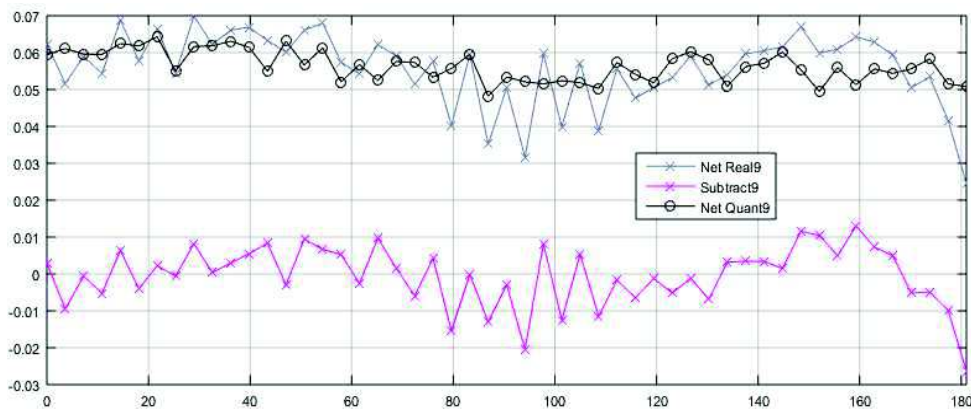
Figure 2. Selected results of comparative studies between the quantum neural network adder net_i for the second neuronal output layer for the nine input and analogue values of the perceptron adder of the ANN. *Source*: Own study in MATLAB and Simulink Environment [Embedded MATLAB™, 2002-2016]

2.2. Quantum-Inspired Evolutionary Algorithms

In the examined neural model of the EPE system, the lowest possible number of factors describing the system was chosen, based on the quotations on the Day Ahead Market (DAM). Two types of quantities were taken: one type at the input, delivered and sold electrical energy (ee) at a given hour of the day [MWh] and one

type at the output of the system, the average price obtained from the sold ee at a given hour [PLN/MWh] [8, 11, 16-17, 21-25].

The data used for modeling were collected from the DAM of the Polish Power Exchange S.A. (PPE, PPE S.A.) in the period from 1 January 2015 to 30 June 2015. A perceptron of ANN (with one hidden layer) was taken to model the EPE system, using the reverse error propagation learning method and tansig(net) activation function for the first neuronal layer expressed by the equation (6) and the second neuronal layer function expressed by pureline(net) [13, 20]:

$$f_a(net) = net, \tag{7}$$

where net is the sum of the weighted input signal.

The grade and quality of the learning of the EPE model was measured by a mean square error (MSE) expressing by means of a distance measure defined as the sum of the squares of the difference between the corresponding values of the average price of the model (y_{mi}) and system (y_{si}):

$$MSE = \sum_{i=1}^{i=n}(y_{mi} - y_{si})^2. \tag{8}$$

The signal waveform shown in Figure 3 concerns the MSE error of the perceptron ANN (EPE neural model) output values relative to the EPE (real data) system output values. During the daily hours the difference ranged from - 0.015 to 0,015.

Next, the ANN model was learned by the EPE system for DAM data, and then was subjected to an evolutionary algorithm to improve the accuracy of the model [16-17].
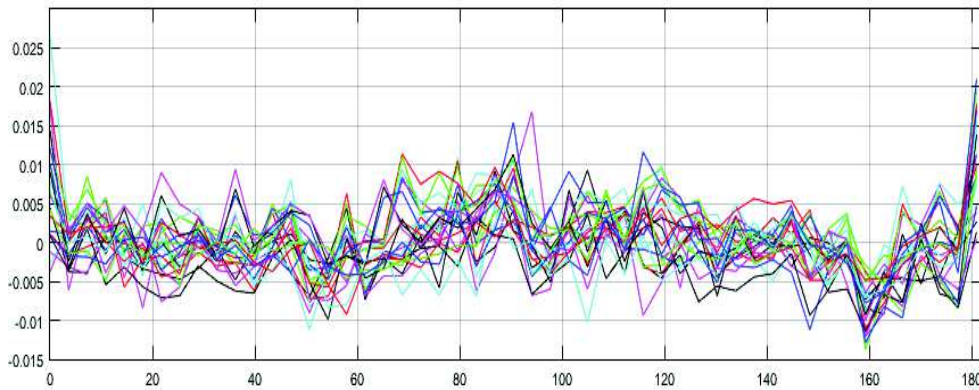

Figure 3. MSE error between output from neural model and output from EPE system. Denotations: x-axis - next day of the period under test, y-axis - Mean Square Error for each 24-hour period. *Source*: Own study in MATLAB and Simulink using NNT [Embedded MATLAB™, 2002-2016]

Selected divergences between model and system responses for selected hours, i.e. the highest for the 18 o'clock, the smallest for hour 23 o'clock and the average 5 o'clock is shown in Figure 4. As can be seen, the model reacts with some delay to changes in the output values of the EPE system, but in a relatively faithful way reproduces its value changes indicating that the evolutionary model is more accurate. Essential alignment of the neuronal-evolutionary model to the EPE system generated in successive iterations of the SEA algorithm took place over four eras, followed by slight changes in accuracy from 0.99832 to 0.99880.

The mutation operator was abandoned because of the unnoticeable changes in modeling accuracy, which was a natural consequence of the very high degree of adaptation of the neuron model to the EPE system, which was 0.9981, thus only the crossing operator was used in the evolutionary algorithm.

In order to further increase the accuracy of the neural model of EPE system, an attempt was taken to use both the ANN as well as the evolutionary algorithm by using quantum computer methods, including mixed quantum numbers and quantum computing method [21-25].
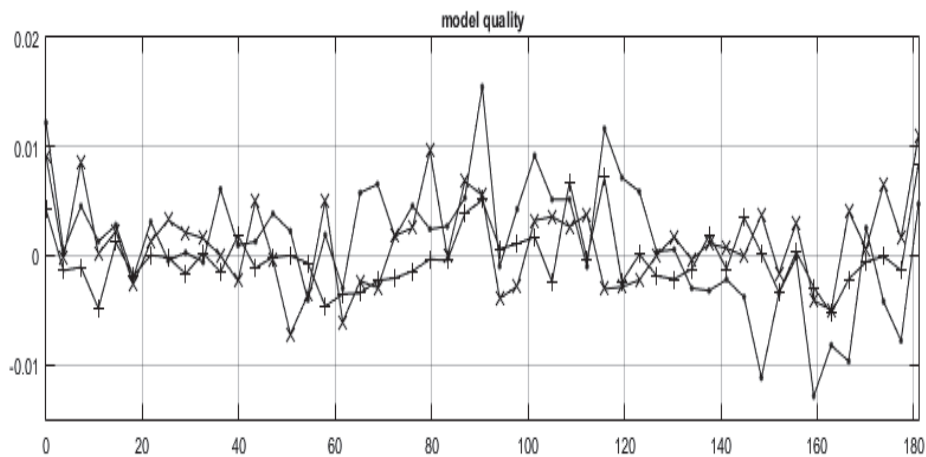

Figure 4. MSE error between exit of neuronal-evolutionary model and exit from EPSM system for three selected hours, i.e. the largest at 18 o'clock the smallest 23 o'clock and the average 5 o'clock. Denotations: axis x - consecutive day of the period under review for the above three hours, y axis - MSE. *Source*: Own study in MATLAB and Simulink using NNT [Embedded MATLAB™, 2002-2016]

Comparison of the neural model and the neural model corrected with Evolutionary Algorithm for the selected hours, i.e. for the 1 o'clock, is shown in Figure 5, and for 13.00 is given in Figure 6. The designed and implemented hybrid model of the EPE system consists of a neural model complemented by an EA and is called the neural evolution model [21-25].

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The EA has improved the parameters of the EPE system model by 0.2% in relation to the real EPE system. Selected comparative studies on the weighted sum (net_i), i.e. weighted quantum adder and weighted neuronal adder for the hidden neuronal layer for measured data at 4 pm o'clock, are given in Figure 7.

In the evolutionary model, it was assumed that the values of the neural model weights are elements of the chromosomes, of which using the EA, the Beginning Population (BP) is built through successive epochs to the Parental Population (PP). Both weighing arrays (**W1** and **W2**) obtained by teaching the ANN model of the EPE system were treated as single individuals consisting of single chromosomes, in which two sub-chromosomes represented by both weights were immersed: **W1** matrix (between the input layer and the hidden layer) and **W2** weight matrix (between the hidden layer and the output layer).
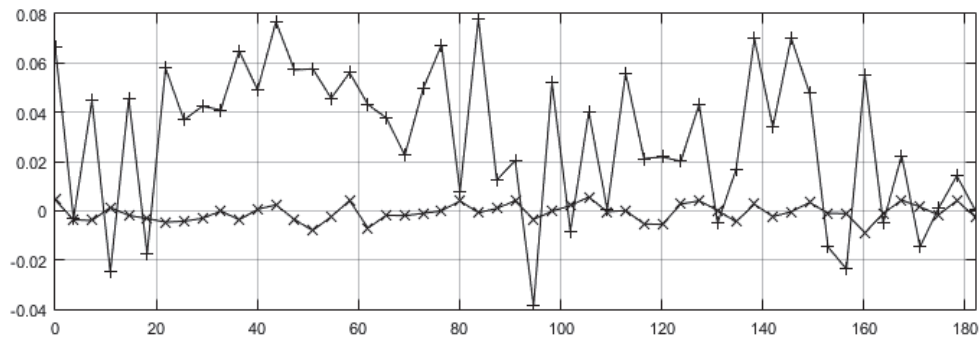
Figure 5. Comparison of modeling obtained with ANN and modified with EA methods, i.e. the average price of ee obtained for the first hour in the period from 01.01.2015 to 30.06.2015 *Source*: Own study in MATLABA and Simulink Environment using Matlab language [Embedded MATLAB™, 2002-2016]
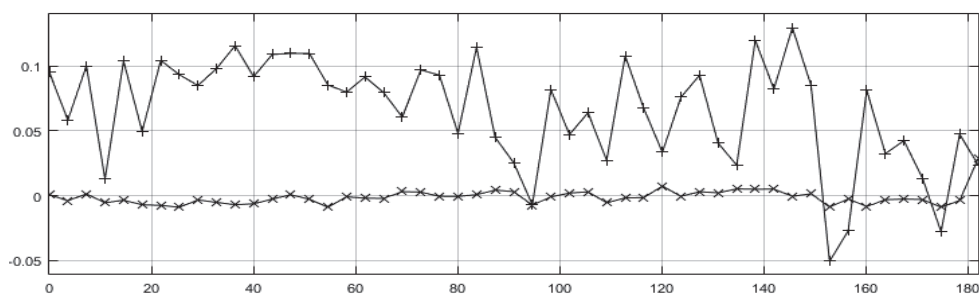
Figure 6. Comparison of modeling obtained with ANN and modified with EA method, i.e. the average price of ee obtained for 1 pm o'clock in the period from 01.01.2015 to 30.06.2015. *Source*: Own study in MATLABA and Simulink Environment using Matlab language [Embedded MATLAB™, 2002-2016].

Then, in the sub-chromosomes, individual rows of both weights were plunged, which consisted of the values of the weights of the individual connections between the neurons, being next to the bias and the parameters of the activation function the basic parameters of the neural model of the EPE. Finally, the chromosome structure at time t was obtained as follow:

$$\mathbf{Ch}_i(t) = \begin{bmatrix} \mathbf{W1} & \mathbf{W2} \end{bmatrix}, \tag{10}$$

where:

$$\mathbf{W1} = \begin{bmatrix} \begin{bmatrix} w_{11,1} & w_{11,2} & ... & w_{11,24} \end{bmatrix} & \begin{bmatrix} w_{12,1} & w_{12,2} & ... & w_{12,24} \end{bmatrix} & [...] & \begin{bmatrix} w_{124,1} & w_{124,2} & ... & w_{124,24} \end{bmatrix} \end{bmatrix},$$

$$\mathbf{W2} = \begin{bmatrix} \begin{bmatrix} w_{21,1} & w_{21,2} & ... & w_{21,24} \end{bmatrix} & \begin{bmatrix} w_{22,1} & w_{22,2} & ... & w_{22,24} \end{bmatrix} & [...] & \begin{bmatrix} w_{224,1} & w_{224,2} & ... & w_{224,24} \end{bmatrix} \end{bmatrix}.$$

As a measure of chromosome adaptation to the environment, the difference between the expected values of the neuron model (t_j) and the mean values of the output signals from the system (y_j) was taken, it was determined as the mean squared error (in this case RMSE) of the form:

$$RMSE = \sum_{j=1}^{n} \sqrt{\frac{1}{n}(t_j - y_j)^2}. \tag{11}$$
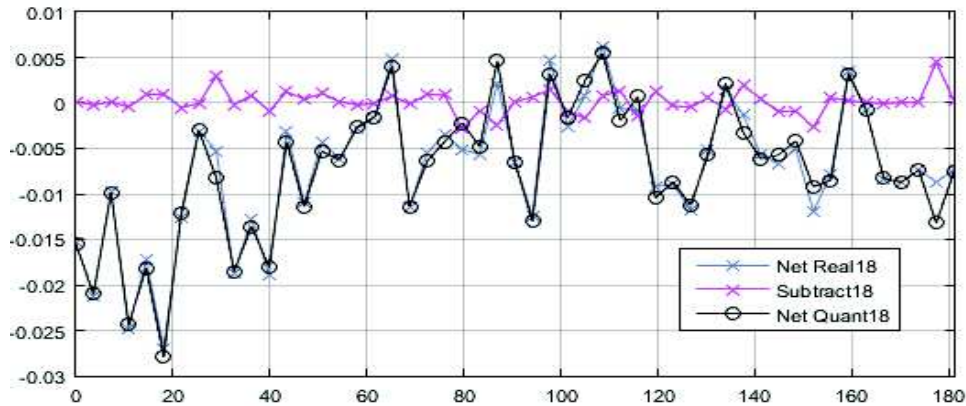
Figure 7. Selected results of comparative studies between neti, i.e., quantum adder and neural adder for the hidden neuronal layer for measured data at 4 pm. Denotations: axis x - time 4 pm on consecutive days in the period from 01.01.2015 to 30.06.2015, y axis: net$_1$ value from hidden layer of ANN for neuron i = 1, Net Quant - net$_1$ value from hidden layer of ANN , Difference - difference between the adders of net$_1$ for the artificial neural network and the Quantum Artificial Neural Network. *Source*: Own study in Simulink Environment

A quantum-evolution algorithm for improving the model parameters of the natural EPE system contains the following basic steps, detailed in the work [19-21]: determination of Quantum Initial Population, defining quantum adaptive functions, matching quantum methods of crossing and mutation and establishing a Quantum method of PP selection. The selection of individuals (chromosomes) for the next generation of the PP was carried out by determining the degree of adaptation of individuals (chromosomes) to the mean value of output (average unit price) on EPE, which was determined by equation (11). In this way, the values of adapting individual chromosomes to the EPE system were determined, and the next, the selection of individuals for the next Parental Population (PP) was performed using the tournament method. After selecting over 10 000 tournament groups, 20 000 of PP individuals were selected [2,11,16-17,21-25].

4. Conclusion

In the following paper, Artificial Neural Network of the Electric Power Exchange model was designed and taught using data from the Day Ahead Market in Poland. In order to increase the accuracy of the generated models of power systems and their subsystems, such as the Electricity Power Exchange, we have designed Evolutionary Algorithm which aided the improvements in the neural models' parameters. Attention has been paid to the new method of quantizing and dequantizing information and methods of quantum computing used in quantum-neural and quantum-evolution models were discussed in detail. The results obtained for the neural model and for the Evolutionary Algorithm inspired by quantum computing were also discussed and were verified on the example of enhancing parameters of the model of the EPE system using quantum mixed numbers. Ultimately, the results aided resolving important issues.

Firstly, the method of improving ANN parameters as a model of a natural appropriate system in Electric Power Exchange for DAM data was developed with the use of quantum solutions.

Secondly, a model of a system was implemented with the use of Matlab language and Neural Network Toolbox [2].

Thirdly, we have developed the assumptions and the method of improving ANN parameters as a model of neural system of EPE using evolutionary algorithms and evolutionary algorithms inspired by quantum computing.

Lastly, appropriate models for comparative studies were constructed and we have carried out comparative studies of neuronal models, evolutionary-neural model and quantum-neural models for real systems using Simulink. With regards to further research, in the next steps simulations and sensitivity tests of neuronal models of the EPE system for untypical input data on DAM should be performed.

REFERENCES

[1] R. de A. Araujo; R.L. Aranildo Junior; A.E.T. Ferreira (2008) *A Quantum-Inspired Intelligent Hybrid method for stock market forecasting,* 2008 IEEE Congress on Evolutionary Computation (IEEE World Congress on Computational Intelligence), 2008, pp.1348–1355.

[2] Embedded MATLAB™ User's Guide © COPYRIGHT 2007 by The MathWorks, Inc. Natick, MA 01760-2098 (USA)

[3] S. L. Ho; S. Yang; P. Ni; J. Huang (2013) *A Quantum-Inspired Evolutionary Algorithm for Multi-Objective Design*, IEEE Transactions on Magnetics, 2013, Volume: 49, Issue 5, pp.1609 – 1612.

[4] K. Han; J. Kim (2000) *Genetic quantum algorithm and its application to combinatorial optimization problem*, Evolutionary Computation, 2000. Proceedings of the 2000 Congress on, Vol. 2, pp. 1354 – 1360.

[5] N. Kasabov (2006) *Neuro-, Genetic-, and Quantum Inspired Evolving Intelligent Systems*, 2006 International Symposium on Evolving Fuzzy Systems, pp. 63 – 73.

[6] H. Kwaśnicka (1999) *Obliczenia ewolucyjne w sztucznej inteligencji*, PWr., Wrocław.

[7] A. Kowalska-Pyzalska (2011), *Koncepcja Smart Grid szansą dla rozwoju generacji rozproszonej*, Prace Naukowe Instytutu Maszyn, Napędów i Pomiarów Elektrycznych Politechniki Wrocławskiej, Nr 65, Studia i Materiały Nr 31.

[8] J. Li, J. Li. (2008) *Next-Day Electricity Price Forecasting Based on Support Vector Machines and Data Mining Technology*. Proceedings of the 27th Chinese Control Conference, Kunming, Yunnan, China, pp. 630 – 633.

[9] G. Liao (2010) *Using chaotic quantum genetic algorithm solving environmental economic dispatch of Smart Microgrid containing distributed generation system problems*, Power System Technology, POWERCON, 2010 International Conference on, pp.: 1 – 7.

[10] Y. Liu Yuanyuan, M. Li (2008) *A bidding method of power market based on immune genetic algorithm*, 27th Chinese Control Conference, pp. 28 - 32

[11] W. Mielczarski (2000) *Rynki energii elektrycznej. Wybrane aspekty techniczne i ekonomiczne*, ARE, Warszawa.

[12] A. Narayanan, M. Moore (1996) *Quantum-inspired genetic algorithms*, Proceedings of IEEE International Conference on Evolutionary Computation, pp. 61-66, IEEE.

[13] S. Osowski (2000) *Sieci neuronowe do przetwarzania informacji*, PW, Warszawa.

[14] M. Parol (red. nauk.) (2013), *Mikrosieci niskiego napięcia*, OW PW, Warszawa.

[15] A. O. Pittenger (2000), *An Introduction to Quantum Computing Algorithms*, Birkhauser, Boston.

[16] D. Ruciński (2017), *The neural modelling of the Electric Power Stock Market*, Studia Informatica. Systems and Information Technology. Systemy i technologie informacyjne, Wyd. UPH, Siedlce.

[17] D. Ruciński (2016), *Neural-evolutionary Modelling of Polish Electricity Power Exchange*, IEEE 2016 Electric Power Networks (EPNet), IEEE XPlore Digital Library, pp. 1-6.

[18] M. Sawerwain, J. Wiśniewska (2016), *Informatyka kwantowa*. WN PWN, Warszawa.

[19] Z. Sheng, J. Wanlu (2012), *A novel quantum genetic algorithm and its application*. Natural Computation (ICNC), 2012 Eighth International Conference on, pp. 613 – 617.

[20] R. Tadeusiewicz, Szaleniec M. (2015), *Leksykon sieci neuronowych*. Wyd. Fundacji „Projekt Nauka", Wrocław.

[21] J. Tchórzewski, D. Ruciński (2017), *Quantum inspired evolutionary algorithm to improve the accuracy of a neuronal model of the electric power exchange*. IEEE EUROCON 2017 -17th International Conference on Smart Technologies, IEEE XPlore Digital Library, pp. 638-643.

[22] J. Tchórzewski, D. Ruciński (2017), *Modeling and simulation inspired by quantum methods of the Polish Electricity Stock Exchange*. 2017 Progress in Applied Electrical Engineering (PAEE). IEEE Xplore Digital Library, pp. 1-6.

[23] J. Tchórzewski, D. Ruciński (2017), *Evolutionary Algorithm Inspired by The Methods Of Quantum Computer Sciences for The Improvement of a Neural Model of the Electric Power Exchange*. Information Systems in Management (ISIM), Vol. 6 (4), pp. 343−355.

[24] J. Tchórzewski (2016), *Systemic Evolutionary Algorithm inspired by methods of quantum computer sciences for the improvement of the accuracy of neural models in electrical engineering and electrical power engineering*. Computer Applications in Electrical Engineering (CAinEE). No. 14/2016. Publishing House of Poznan University of Technology, pp. 280-296.

[25] J. Tchórzewski, D. Ruciński (2016), *Quantum inspired evolutionary algorithm to improve parameters of neural models on example of polish electricity power exchange*, IEEE 2016 Electric Power Networks (EPNet), IEEE XPlore Digital Library, pp. 1-8.

[26] J. Tchórzewski (2013), *Rozwój systemu elektroenergetycznego w ujęciu teorii sterowania i systemów*, OW PWr, Wrocław.

[27] J. Tchórzewski (1990), *Cybernetyka życia i rozwoju systemów*. Monografie nr 22, Akademia Podlaska, Siedlce 1990.

[28] S. Wierzchoń, M. Kłopotek (2015), *Cluster analysis*. Monografie. Wyd. IPI PAN. Warszawa.

[29] S. Węgrzyn, L. Znamirowski (2007), *Zarys nanonauki i informatycznych molekularnych nanotechnologii*, Wyd. PŚ, Gliwice.