QUANTUM-INSPIRED METHOD OF MODELING THE NEURONAL DAY-AHEAD MARKET OF THE POLISH ELECTRICITY EXCHANE

Jerzy Tchórzewski

Dr Hab. Eng. University Professor, University of Natural Sciences and Humanities in Siedlce , Institute of Computer Science

Dariusz Ruciński

PhD Student at Institute of Computer Science, University of Natural Sciences and Humanities in Siedlce

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Agenda

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Introduction to previous works

- The Artificial Neural Network was designed and trained as a model of the Polish Electricity Power Exchange using the Day-Ahead Market (DAM) data.
- Then, it was proposed to modify it by introducing Evolutionary Algorithms, which was then verified using numerical examples.
- It was based on problems related to the improvement and accuracy of the parameters of the neural-evolutionary model.

- For the development of a quantum-evolutionary algorithm, an own methodology for determining mixed quantum numbers has been introduced.
- For the needs of the development of the quantum-evolutionary model own procedures was designed.
- Quantum ANN training was conducted based on the designed procedures.
- Currently, research is continued to determine the degree of improvement and to prove the accuracy of chosen method.

Purpose of current work

- Current paper presents selected elements of the:
  - method of quantization of real numbers in decimal notation into quantum mixed numbers,
  - method of quantum calculations using linear algebra and vector-matrix calculus,

- method of quantum mixed numbers dequantization into real numbers in decimal notation.

Basics of quantum inspired computing

- In the quantum calculations conducted in this study, the basic concepts of linear algebra and vector-matrix calculus were used.
- the possibility of using the probability theory in determining quantum mixed numbers, i.e. quantum numbers residing in many different states at the same time were used.
- linear operator were used to measure the values of the eigenvectors performed on quantum states.

$2 \cdot \alpha^2 = 1,$

System quantization method

- A systemic method of converting real numbers into decimal notation to quantum numbers by using the probability modules of a quantum mixed number and the superposition principle was developed as follow:

- the probability modules were assumed to be equal: α = β, and rule $|\alpha|^2 + |\beta|^2 = 1$ so:

$$2 \cdot \alpha^2 = 1,$$

- from which

$$\alpha = \frac{\sqrt{2}}{2},$$

- Due to the equality of both probability modules, this value approximately is:

$$\alpha = \beta \approx 0{,}71,$$

- Thus, in the case when the dominant state is ket 0, then the values of the probability modulus α are from the interval:

$$0.71 \leq \alpha \leq 1$$

Dequantization with ANN

- the definition of the system state was taken as the basis for determining mixed states of a quantum number
- It is convenient to interpret quantum calculations as the form of the model of a single ANN neuron, described for example by the activation function of the sigmoid tangent of the i-th neuron in the k-th weight layer of the Perceptron Artificial Neural Network

$$y(net_i^k(t)) = \frac{1 - e^{-2\begin{bmatrix} net_{i\,\mathrm{lim}}^k & net_{i,lm}^k \\ net_{i,lm}^k & net_{i,lm}^k \end{bmatrix}}}{1 + e^{-2\begin{bmatrix} net_{i\,\mathrm{lim}}^k & net_{i,lm}^k \\ net_{i,lm}^k & net_{i,lm}^k \end{bmatrix}}},$$

where:

net_i^k – quantum adder of the i-th neuron in the k-th layer of neurons weights, determined as the sum of the weighted quantum values of the input signals fed to the k-th layer of neurons,

$net_{i,lm}^k$ - element of adder net^k_i with the index l_m as a quantum weighted input signal to the k-th neuron layer of an artificial neural network with a pure nature resulting from two mixed states (input mixed quantum number and mixed weight quantum number),

Example of use the dequantization formula

$$y_1^1(net_1^1(t)) = \frac{\begin{bmatrix} 0{,}0860 & 0{,}9964 & . & 0{,}0848 & \dots & 0{,}0862 \\ 0{,}9962 & 0{,}0845 & . & 0{,}9963 & \dots & 0{,}9962 \end{bmatrix} - \begin{bmatrix} 0{,}9963 & 0{,}0867 & . & 0{,}9963 & \dots & 0{,}08569 \\ 0{,}0855 & 0{,}9962 & . & 0{,}0851 & \dots & 0{,}9963 \end{bmatrix}^{-\begin{bmatrix} 92{,}9226 & 42{,}547 \\ 42{,}7272 & 27{,}0664 \end{bmatrix}}}{\begin{bmatrix} 0{,}0860 & 0{,}9964 & . & 0{,}0848 & \dots & 0{,}0862 \\ 0{,}9962 & 0{,}0845 & . & 0{,}9963 & \dots & 0{,}9962 \end{bmatrix} - \begin{bmatrix} 0{,}9963 & 0{,}0867 & . & 0{,}9963 & \dots & 0{,}08569 \\ 0{,}0855 & 0{,}9962 & . & 0{,}0851 & \dots & 0{,}9963 \end{bmatrix}^{-\begin{bmatrix} 92{,}9226 & 42{,}547 \\ 42{,}7272 & 27{,}0664 \end{bmatrix}}}.$$

- Dequantization is the conversion of quantum mixed numbers into real numbers in decimal notation.
- Since the nature of the ANN quantum model results from the matrix power, the dequantization of a quantum mixed number into real (or complex) numbers comes down to solving the research problem consisting in the ability to raise the matrix to the matrix power

or to the ability to bring the obtained result to a decomposable state described by equation

Quantum inspired computing

- In quantum calculations, the matrix form of operators and vectors are performed in so-called finite-dimensional Hilbert space.
- Dirac notation convention was adopted to simplify notations and calculations.
- The quantum computation process use the input data to the quantization process and the weights of the neural model also were subjected to the quantization process.
- Selected activation functions, such as **tansig()** type functions, was carried out on the basis of an algorithm including the following basic steps

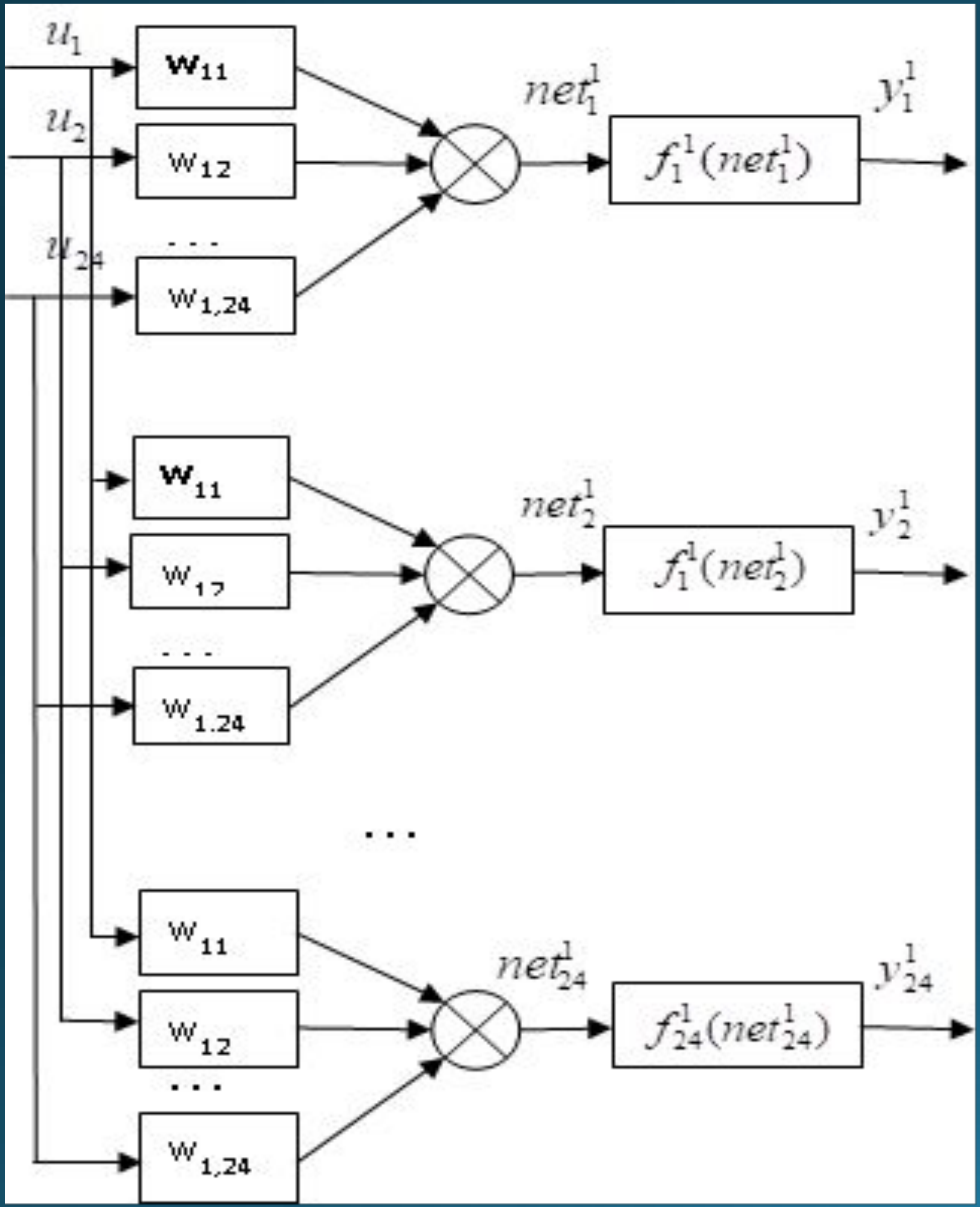

Fig. 1. Block diagram of the net_i^k adder for the first layer of the DAM neural model. Symbols: u_1 ... u_{24} - ANN input signal (here the value of the volume of electricity supplied and sold in each of the 24 hours of a day) in [MWh], y_1 - ANN output signal (here volume-weighted average unit price for electricity supplied and sold in at a given hour of the day, in (PLN/MWh), w_{11}, w_{12}… $w_{1,24}$ - ANN weights.

- In quantum calculations, the matrix form of operators and vectors, the so-called finite-dimensional Hilbert space, hence each state of a quantum mixed number in a Hilbert space H2 corresponds unambiguously to the matrix of the form:

$$l_m = \begin{bmatrix} \alpha \\ \beta \end{bmatrix},$$

- hence a quantum mixed number corresponding to a binary number will be expressed as:

$$l_m = \begin{bmatrix} \alpha_1 & \alpha_2 & \dots & \alpha_n \\ \beta_1 & \beta_2 & \dots & \beta_n \end{bmatrix}.$$

- When calculating matrices, a vector-matrix calculus can be used, which is associated with appropriate addition, multiplication, transposition of matrices, etc. (see: Kaczorek, 1998).

- At this point, it is also worth supplementing the Dirac notation convention, which simplifies notations and facilitates calculations.

- Well, in the case of a quantum register, the value of the expression $|\alpha\rangle$, where α is a variable whose values are natural numbers, should be read like a notation in the binary system supplemented with zeros on the left side to the length of n characters, which leads to the notation (see : Susskind, Friedeman, 2016; Sawerwain, Wisniewska, 2015):

$$\left|\phi\right\rangle = \sum_{k=0}^{2^n-1} \alpha_k \left|k\right\rangle$$

where the α_k coefficients meet the normalization conditions (the sum of squared modules equals 1).

The quantum computation process using the input data subjected to the quantization process and using the weights of the neural model also subjected to the quantization process and appropriately selected activation functions, such as tansig() type functions, was carried out on the basis of an algorithm including the following basic steps (Tchórzewski, Ruciński, 2016; Ruciński, 2018):

- **Step 1.** Converting real numbers in decimal notation to quantum mixed numbers using the system quantization method.

- **Step 2.** Determining weighted adders for individual outputs from the first layer of neurons, e.g. multiplication of the first mixed quantum number w11 and the mixed quantum number of the input quantities u1 for neuron 1 in layer 1 for the first training pair, i.e. two quantum mixed numbers:

$$net_1^1 = w_{11}^1 \cdot u_1,$$

where

$$w_{11}^{1}=\begin{bmatrix}0,8256 & 0,8285 & 0,8294 & 0,8251 & 0,4162 & 0,8292 & 0,8305 & 0,8249 & 0,8294 & 0,4196 & 0,8294 & 0,8312 & 0,8311 & 0,8277 & 0,8295 & 0,8297 & 0,8333\\ 0,4175 & 0,4140 & 0,4141 & 0,4181 & 0,8267 & 0,4132 & 0,4116 & 0,4184 & 0,4129 & 0,8265 & 0,4129 & 0,4108 & 0,4109 & 0,4149 & 0,4128 & 0,4125 & 0,4081\end{bmatrix}$$

$$u_{1}=\begin{bmatrix}0,8256 & 0,8285 & 0,8294 & 0,8251 & 0,4162 & 0,8292 & 0,8305 & 0,8249 & 0,8294 & 0,4196 & 0,8294 & 0,8312 & 0,8311 & 0,8277 & 0,8295 & 0,8297 & 0,8333\\ 0,4175 & 0,4140 & 0,4141 & 0,4181 & 0,8267 & 0,4132 & 0,4116 & 0,4184 & 0,4129 & 0,8265 & 0,4129 & 0,4108 & 0,4109 & 0,4149 & 0,4128 & 0,4125 & 0,4081\end{bmatrix}$$

As a result of the multiplication of the above two quantum mixed numbers in a matrix form, a square matrix with a dimension of 2 x 2 for each neuron in the first layer was achieved (and then in a similar way in the second layer):

$$net_i^k(t)=\sum_{i,lm,k}\begin{bmatrix}net_{i\lim}^{k} & net_{i,lm}^{k}\\ net_{i,lm}^{k} & net_{i,lm}^{k}\end{bmatrix},$$

- For example for the first neuron of the first layer the following is obtained:

$$net_1^1(t) = \begin{bmatrix} 11,6712 & 5,9219 \\ 5,4275 & 3,2112 \end{bmatrix} + \ldots + \begin{bmatrix} 11,1596 & 5,3631 \\ 5,9722 & 2,2569 \end{bmatrix} = \begin{bmatrix} 46,4663 & 21,7725 \\ 21,9636 & 12,5232 \end{bmatrix}.$$

- **Step 3**. Finding the value of the activation function as a tansig () function for the first layer of neurons and purlin() for the second layer neurons.

- Determining the activation function for individual outputs from the first layer of neurons (and analogically from the second layer of neurons)

$$y_1^1(net_1^1(t)) = \frac{1 - e^{-2\cdot\begin{bmatrix}46,4663 & 21,7725\\ 21,9636 & 12,5232\end{bmatrix}}}{1 + e^{-2\cdot\begin{bmatrix}46,4663 & 21,7725\\ 21,9636 & 12,5232\end{bmatrix}}} = \frac{1 - e^{-\begin{bmatrix}92,9226 & 42,547\\ 42,7272 & 27,0664\end{bmatrix}}}{1 + e^{-\begin{bmatrix}92,9226 & 42,547\\ 42,7272 & 27,0664\end{bmatrix}}} =$$

$$= \frac{\begin{bmatrix}0,0860 & 0,9964 & . & 0,0848 & \ldots & 0,0862\\ 0,9962 & 0,0845 & . & 0,9963 & \ldots & 0,9962\end{bmatrix} - \begin{bmatrix}0,9963 & 0,0867 & . & 0,9963 & \ldots & 0,08569\\ 0,0855 & 0,9962 & . & 0,0851 & \ldots & 0,9963\end{bmatrix}^{-\begin{bmatrix}92,9226 & 42,547\\ 42,7272 & 27,0664\end{bmatrix}}}{\begin{bmatrix}0,0860 & 0,9964 & . & 0,0848 & \ldots & 0,0862\\ 0,9962 & 0,0845 & . & 0,9963 & \ldots & 0,9962\end{bmatrix} - \begin{bmatrix}0,9963 & 0,0867 & . & 0,9963 & \ldots & 0,08569\\ 0,0855 & 0,9962 & . & 0,0851 & \ldots & 0,9963\end{bmatrix}^{-\begin{bmatrix}92,9226 & 42,547\\ 42,7272 & 27,0664\end{bmatrix}}}.$$

- **Step 4.** Due to the existence of the matrix as an exponent of the function e (written in the activation function as a quantum mixed number), the function was dequantized by means of the learned ANN dequantization.

- The value of expression becomes the input value for the layer 2 of the ANN neurons, which can also be determined analogously to the first layer.
- The outputs from the remaining neurons of the first layer (hidden layer) and the second layer (output layer) are determined in a similar way.
- The vector of quantum outputs from the output layer is also used in the clotting function for assessment of the evolutionary algorithm for each individual from the parental population, e.g. in relation to the average value of all individuals.

Conclusions and directions for further research

- We proposes new aspects of quantum inspiration for modeling systems using, in particular, artificial neural networks previously tuned with evolutionary algorithms.
- The conducted research required the use and implementation of appropriate new methods: quantization of real numbers in decimal notation, quantum computations using matrix-vector calculus, and building, implementing and teaching ANN dequantization.
- The constructed models satisfactorily illustrate the behavior of the PEPE system for the DAM.

- The attempts to improve the classic ANN model have shown that the improvement of the quality of the model with methods appropriate for the classical Evolutionary Algorithms gave positive results.

- In the case of methods inspired by quantum computing, attempts were made to propose their own solutions based on linear algebra and vector-matrix calculus in Hilbert space.

- The designed and implemented hybrid model of the DAM system consists of a neural model (Perceptron ANN), with weights modified by AE (neural-evolutionary model), which improved the parameters of the DAM system

- The designed and implemented hybrid model of the DAM system consists of a neural model (Perceptron ANN), with weights modified by AE (neural-evolutionary model),

which improved the parameters of the DAM PPE system model in the range from - 0.17% to 0, 18% to the range from -0.11% to 0.12%,

and the designed and implemented AE-assisted and quantum-inspired neural model (neural-evolution-quantum model) improved the parameters of the model from -0.11% to 0.12 % to the range of -0.04% to 0.05%,

i.e. an order of magnitude, ignoring the fact that the MSE error for the Perceptron ANN was already relatively low.

- The conducted research will be continued in the scope of testing the applied quantum inspiration method on other examples of neural modeling in order to check its effectiveness and efficiency,

including on such examples as e.g. quantum-inspired neural modeling of the development of the Polish Electric Power Exchange carried out with the use of relatively large training and testing files.

Thank You for attentions

Questions ???

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