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# HYBRID NEURON NETWORKS BASED ON Q- , W- AND CLASSICAL NEURONS

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***Abstract****—The problem of structural-parametric synthesis of hybrid neural network based on the use of multilayer perceptron topology is considered. Hybridization is achieved through the use of artificial neurons of different types, namely Q-neuron, W-neuron and classical neuron. The problem of optimal selection of the number of layers, neurons in layers, as well as the types of neurons in each layer and the principles of alternating them using the genetic algorithm SPEA2 is solved. Examples of building a hybrid neural network using this methodology and a given optimization criterion for solving classification and forecasting problems are given.*

**IndexTerms—**Hybrid neural network; structural-parametric synthesis; optimization problem.

## I. INTRODUCTION

Nowadays, there is undoubtedly considerable scientific and practical interest in computing structures of a new type - artificial neural networks. It is due to a number of successful applications of this new technology that has allowed us to develop effective approaches to solving problems in a context of structural and parametric uncertainty that was considered difficult to implement on traditional computers. The success of artificial neural networks is due, in the first place, to universal approximation properties, parallel processing of data, and the ability to obtain a valid result based on the data used in the learning process. At the same time during the learning process, it is important to note the settings of hyperparameters, such as the values of synaptic weights and parameters of the activation function, and the network topology as a whole.

The greatest interest is in solving the problems of classification and forecasting, since they have a wide range of practical applications. There are a huge variety of neural architectures. As a rule, any architecture has its own disadvantages and advantages. Hybridization of networks is one of the ways to solve the disadvantages of a particular architecture. That is, it is a combination of several neural networks (NMs) for a given task. This allows a complex task to be broken down into simpler subtasks, and the NM architecture can be optimized for a specific task. But there is a difficulty in selecting the topology of a hybrid neural network (HNN), as there are many types of neural networks and to determine the combination of which types will best solve the problem. There is a need to solve the problem of parametric synthesis of HNN.

## II. PROBLEM STATEMENT

The problem of structural-parametric synthesis of HNN has two methods of solution: the first method is the determination of the topology of the neural networks that are part of the HNN, based on the solution of the optimization problem, and the second – the optimal determination of the topology of different neurons that are part of the NM of one topology .

This paper uses a second approach. The classification of artificial neurons topologies is presented in Fig. 1.

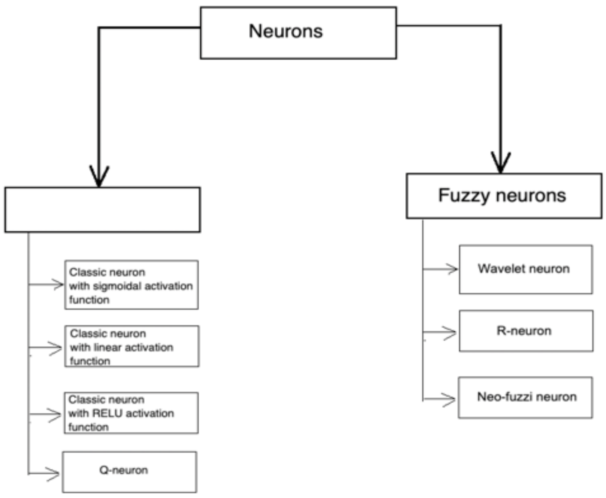


Fig. 1. Classification of neurons

Consider the following neuron topologies: classical neuron, *Q*-neuron, wavelet neuron, which can be used to create HNNs.

The mathematical model of the classical neuron (Fig. 2) has the following form

$$x_i = f\left(b + \sum_{i=1}^{n} x_i w_i\right),$$

where $x(n \times 1)$ is the vector of inputs; $w(n \times 1)$ is the vector of weights; $b$ (bias) is the offset; $f(.)$ is the activation function. Figure 2 is a block diagram of a neuron.

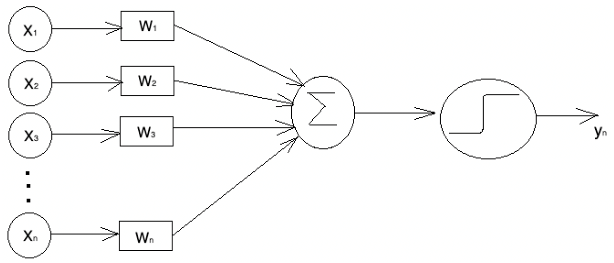


Fig. 2. Architecture of the classic neuron

Next, consider a *Q*-neuron or a quadratic neuron. The main difference from a classical neuron is the use of conventional linear inputs and their quadratic combinations as input signals. Thus, the number of weights becomes larger and the learning time increases, but this neuron exhibits much more dependencies in the data than the classical one. The mathematical model of *Q*-neuron has the following form:

$$y_i = \theta_j + \sum_{i=1}^{n} w_{ji} x_i + \sum_{p=1}^{n} \sum_{l=1}^{n} w_{jpi} x_p x_i,$$

where $w_{ji}$ is the weight at the input signals, $x_i$ is the input signal; $w_{jpl}$ is the weight of the quadratic input combinations; $x_p$ and $x_l$ is the corresponding quadratic combination; $\theta_j$ is the bias (Fig. 3).

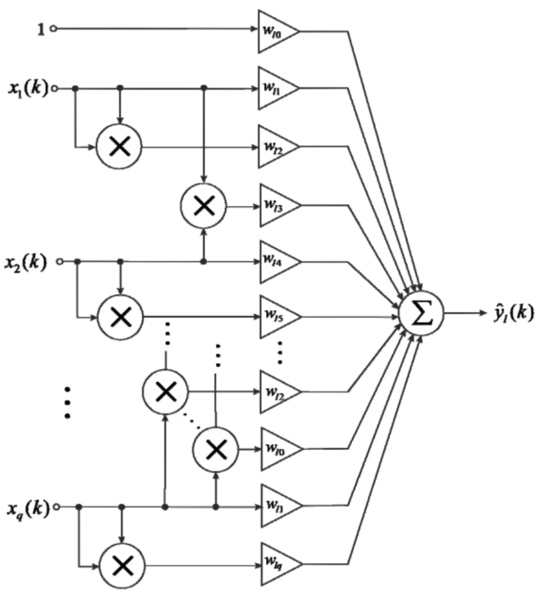

Fig. 3. *Q*-Neuron Architecture

According to the classification, consider the architecture of the wavelet neuron (Fig. 5)

The mathematical model of a wavelet neuron has the form [1]

$$\hat{y} = \sum_{i=1}^{n} f_i(x) = \sum_{i=1}^{n} \sum_{j=1}^{h_i} w_{ji} \varphi_{ji}(x_i),$$

where $w_{ji}$ is the weighting coefficients of the membership functions; $\varphi_{ji}$ are membership functions, and $i = 1...n$, where $n$ is the number of wavelet synapses in a neuron, a $j = 1...h$, where $h$ is the number of activation functions in each synapse.

$$\varphi_{ji}(x_i)(1 - \alpha_{ji} t_{ji}^2 \exp\left(-\frac{t_{ji}^2}{2}\right),$$

where $t_{ji} = (x_i - c_{ji})\sigma_{ji}^{-1}$, $c_{ji}$ is the center parameter; $\sigma_{ji}$ is the width parameter and $\alpha_{ji}$ shape parameter. And the wavelet synapse is:

$$\sum_{j=1}^{h_i} w_{ji} \varphi_{ji}(x_i),$$

$i = 1...n$ where $n$ is the number of wavelet synapses in a neuron, a $j = 1...h$, where $h$ is the number of activation functions at each synapse.

Unlike the neo-fuzzi neuron, the width, center, and shape parameters are determined during training [2].

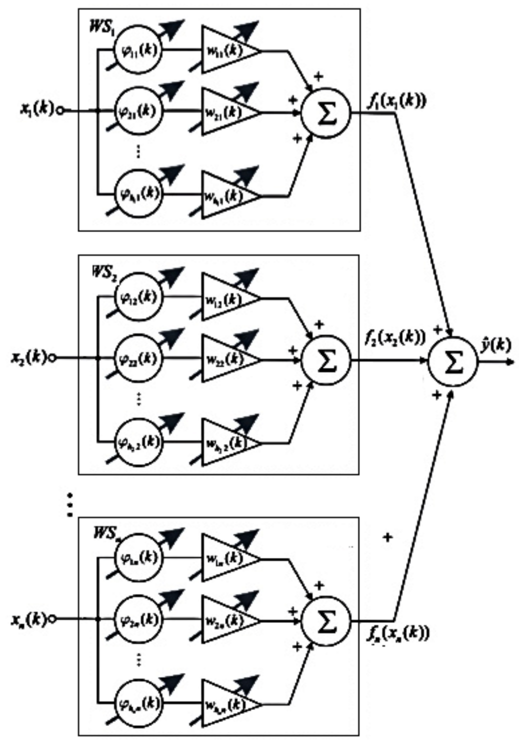

Fig. 5. Wavelet neuron architecture where $\varphi_i(x)$ is the output $i$ synapse wavelet, $WS_i - i$ synapse wavelet

As the topology of the neural network for the construction of HNN, as an example, choose perceptron.

The problem of structural-parametric synthesis of HNN is posed, which consists in the optimal choice of the number of layers, the number of neurons in the layers, the order of alternation of layers with different neurons.

Generalized error is selected as the optimization criterion:

$$E(n) = \frac{1}{2}\sum_{j\in C} e^2(n),$$

where $e_j(n)$ is the error signal of the original $j$ neuron at the $n$ iteration and is determined by the ratio

$$e_j(n) = d_j(n) - y_j(n).$$

## III. OVERVIEW OF METHODS

In papers [3], [5] proposed the modification of the architecture of a multilayer hybrid GMDH-neural network by introducing hybrid *Q*-neurons and *W*-neurons into the node structure, which allowed to increase the approximate properties of the GMDH-neural networks, increase the number of inputs to the network node, optimize the structure of the hybrid network in the learning process.

In paper [4], a cascade GMDH-wavelet-neuro-fuzzy network was proposed. As nodes of such a network are distinguished *R*-neurons with the function of Epanechnikov activation and block adaptive fuzzy wavelets with adaptive wavelet function of membership. Was proposed the training algorithms, which have tracking and filtering properties, allow to adjust not only synaptic scales but also the parameters of the activation-belonging function in online mode.

Thus, the problem statement is new.

## IV. PROBLEM SOLUTION

To solve this problem, we use a genetic algorithm, namely SPEA2 [6]. The structure of the chromosome consists of the following parameters: the type of neuron (*Q*-neuron, wavelet neuron, perceptron), the number of neurons of one species in a particular layer and depending on the type of neuron the type and parameters of the activation function (membership).

1) The algorithm for solving the problem of structural-parametric synthesis of HNN based on the use of genetic algorithm has the following form:

2) Set the initial iteration number $i = 1$

3) Form *i*-layer perceptron and solve the optimization problem of the optimal choice neuron type (*Q*-neuron, wavelet neuron, perceptron), the number of neurons of one species in a particular layer and depending on the type of neuron the type and parameters of the activation function (membership) and the values of the weight coefficients.

4) If the generalized error for the NN found on the test data satisfies the set threshold then the learning process ends otherwise we proceed to point 4.

5) Form $(i+1)$-layer perceptron and optimally using GA choice neuron type (*Q*-neuron, wavelet neuron, perceptron), the number of neurons of one species in a particular layer and depending on the type of neuron the type and parameters of the activation function (membership) $(i+1)$-layer and the values of the weight coefficients of the first and second layers (recalculation of the values of the weight coefficients of the first *i*th layers are repeated)

6) Repeat steps 3 and 4 until the optimal topology is found

The solution algorithm is represented by the pseudocode below

```
# create a single-layer network and write down its parameters

best_network = SPEA2.get_one_layer()
best_network.train()
best_loss = best_network.get_loss()
best_params = [best_network.get_params()]

for it in range(number_iterations):
    # form a network of layers that were found in previous iterations
    for i in best_params:
            cur_network +=
            get_layer_from_params(i)
    cur_network += SPEA2.get_one_layer()

    # train it
    cur_network.train()

    # check if the error is less than the best
    if cur_network.get_loss() < best_loss:
     # if the error is smaller, then we update the best network, the best error and add the last layer - the configuration of this iteration

      best_params.append(
      cur_network.get_params())
      best_loss = cur_network.get_loss()
    else:
      # otherwise, if the error is not smaller, then the best network was found in the previous iteration, we complete the search
      break
```

## V. RESULTS

The results of the solution of the problem of structural-parametric synthesis of HNN are considered in the example of the problem of classification and forecasting.

A sampling of handwritten numbers from [7] was used for the classification task.

The results of the operation of the optimal HNN according to the criterion of generalized error in solving the classification problem are presented in Table I.

TABLE I. RESULTS OF SOLVING THE CLASSIFICATION PROBLEM

| **Number of layers** | **Type of neuron of a particular layer** | | | **Generalized error** |
|---|---|---|---|---|
| | ***1st layer*** | ***2nd layer*** | ***3rd layer*** | |
| 3 | *Q*-neuron (64 neurons) | Classic neuron (32 neurons) | *Q*-neuron (16 neurons) | 0.120621 |

The sample with the lowest temperatures was used for the forecasting task [8]. This sample has a minimum temperature for each day for a specified period. Sampling takes 64 consecutive days to enter the neural network and the next 65 days to exit the neural network.

The results of the experiments on the forecasting problem are presented in Table II.

TABLE II. RESULTS OF SOLVING THE FORECASTING PROBLEM

| **Number of layers** | **Type of neuron of a particular layer** | | | **Generalized error** |
|---|---|---|---|---|
| | ***1st layer*** | ***2nd layer*** | ***3rd layer*** | |
| 3 | Classic neuron (64 neurons) | Wavelet neuron (32 neurons) | Wavelet neuron (16 neurons) | 0.008060 |

## VI. CONCLUSION

The results of HNN synthesis showed that different tasks required different topologies of hybrid neural networks, the classification was better shown by the coupling of the perceptron and Q-neuron, and on the contrary, the wavelet neuron performed much better.

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**О. І. Чумаченко, С. Т. Дичко, А. Р. Рижий. Гібридна нейронна мережа на основі Q-, W-, класичних нейронів**

Розглянуто задачу структурно-параметричного синтезу гібридної нейронної мережі на основі використання топології багатошарового персцептрону. Гібридизація досягається за рахунок використання штучних нейронів різних типів, а саме Q-нейрону,W-нейрону і класичного нейрону. Розв’язано задачу оптимального вибору кількості шарів, нейронів в шарах, а також типів нейронів у кожному шарі та принципи їх чергування за допомогою генетичного алгоритму SPEA2. Наведено приклади побудови гібридної нейронної мережі за даною методологією та заданим критерієм оптимізації для розв’язання задач класифікації та прогнозування.

**Ключові слова:** гібридна нейронна мережа; структурно-параметричний синтез; проблема оптимізації.

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**Е. И. Чумаченко, С. Т. Дычко, А. Р. Рыжий. Гибридная нейронная сеть на основе Q-, W-, классических нейронов**

Рассмотрена задача структурно-параметрического синтеза гибридной нейронной сети на основе использования топологии многослойного персцептрону. Гибридизация достигается за счет использования искусственных нейронов различных типов, а именно Q-нейрона, W-нейрона и классического нейрона. Решена задача оптимального выбора количества слоев, нейронов в слоях, а также типов нейронов в каждом слое и принципы их чередования с помощью генетического алгоритма SPEA2. Приведены примеры построения гибридной нейронной сети по данной методологии и заданным критерием оптимизации для решения задач классификации и прогнозирования.

**Ключевые слова:** гибридная нейронная сеть; структурно-параметрический синтез; задача оптимизации.

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