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IMPROVEMENT OF CONTROL METHOD OVER THE ENVIRONMENT OF COGNITIVE RADIO SYSTEM USING A NEURAL NETWORK

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В ході досліджень вдосконалено метод управління середовищем когнітивного радіо і було здійснено впровадження когнітивних функцій в її архітектуру. Запропоновано архітектуру управління середовищем WRAN з використанням когнітивних функцій, а також розроблено блок-схему алгоритму управління середовищем WRAN, реалізованого під управлінням нейронної мережі

Ключові слова: когнітивне радіо, архітектура, радіочастотний ресурс, нейронна мережа, імовірнісна нейронна мережа

В ходе исследований был усовершенствован метод управления средой когнитивного радио и выполнено внедрение когнитивных функций в её архитектуру. Предложена архитектура управления средой WRAN с использованием когнитивных функций, а также разработана блок-схема алгоритма управления средой WRAN, реализованная под управлением нейронной сети

Ключевые слова: когнитивное радио, архитектура, радиочастотный ресурс, нейронная сеть, вероятностная нейронная сеть

1. Introduction

Many WRANs (Wireless Regional Area Networks) of the same type have been deployed in recent years within a small territorial proximity. Different WRANs in a particular area can be deployed by different providers.

In such a dynamically growing environment, a large number of problems arise related to security, coexistence, network topology, etc. All providers must coordinate their actions so that users can share the same resources in different WRANs. Control over the environment in a cognitive radio system requires a detailed consideration of the functions of spectrum management and radio communication with programmable parameters. Such control is implemented at the physical layer (PHY) in line with the IEEE 802.22 standard. Wireless local area networks (WRANs) are an important component of cognitive radio platforms.

There are different models to construct WRANs systems. Hardware tools that make it possible to carry out development of strategy for resource allocation have been implemented on their basis.

Results of the research imply the introduction of modern cognitive functions to the existing architecture, the creation of a flow chart for the environment control algorithm using a neural network to achieve information allocation and distributed solution among the multitude of WRANs. Providers of WRAN can work under two modes. The first one is a self-organizing regime under which a cognitive radio network (CR) performs tuning, network analysis and organizes coexistence with the functioning WRANs. The second one is a manual mode under which providers establish service level agreements with each other (volume of information, signal strength, security, etc.).

Thus, the relevance of present work is determined by the need to solve the problems arising in the course of control over the environment of a cognitive radio system in order to improve the efficiency of their functioning.

2. Analysis of the published data and problem statement

Cognitive radio of the IEEE 802.22 standard is designed to solve such communication problems as: limited frequency resource [1], dynamic access to the environment [2], decentralized management of network resources [3]. The standard is expected to be used in the regional wireless networks (WRANs). At present, there are a lot of methods to control the environment: systems with a centralized controller [4], decentralized systems [5], self-organizing systems [6], multiagent systems [7]. The main disadvantages of these methods are:

– redundancy of the software and technical means for the allocation of information flows between network nodal elements;

– low fault tolerance of the system;

– absence of accumulation of the accepted right and wrong decisions;

– lack of mechanisms for the implementation of dynamic change in the environment;

– decrease in productivity and increase in the cost of deployment of a radio system due to increase in scalability.

For the further development and implementation of cognitive radio, a number of improvements have to be carried out to eliminate the above shortcomings, and it is also proposed to consider a neural network as a method to improve control over cognitive radio environment.

The architecture of the cognitive network is not considered in paper [8]. Some elements of the architecture and their interactions are described, such as security, the script of initialization of frequencies, validation. In [9], the architecture of WRAN is partially considered. There are no basic elements of the network. Methods of control, training and frequency analysis are not considered. In [10], separate blocks of the physical level of cognitive radio are considered. In article [11], the architecture is considered and a reference is given to the architecture in line with the IEEE 802.22 standard, but in the standard the development of these elements is assigned to the provider's and integrator's sides, and it is considered only superficially.

In addition, some methods have a complex software or technical component, others have low fault tolerance or lack of accumulated solutions. Cognitive functions (analysis of the environment, application of experience, learning systems) are practically not implemented, or possess a cumbersome structure. Given the aforementioned, there is a need to study a system that maximally eliminates the shortcomings considered using cognitive functions. As a result of the analysis performed, a PNN neural network has been selected for the present study.

3. The aim and objectives of the study

The objective of present research is within the field of algorithms for the functioning and architecture of a cognitive radio system and implies improvement of the method to control the environment of cognitive radio using a probabilistic neural network (PNN), as well as its implementation.

To achieve the set objective, the following tasks were defined:

– development of the WRAN environment control architecture using a neural network;

– development of a flow chart for the environment control algorithm using a neural network;

– PNN simulation as a decision-making subsystem to control the environment of a cognitive radio system.

4. Methods to study a control system

Fig. 1 shows an improved environment control architecture for WRAN using a neural network. A variety of different WRANs are located together in a specific geographic area. A neural network is located in each base station (BS) and interacts with other WRANs in line with the IEEE 802.22 standard. The network environment may include other WRANs with which it can interact. These interactions can include data sharing and resource allocation coordination. A separate network may act as a coordinator of the environment and interact with multiple WRANs to ensure the claimed cognitive radio characteristics described in [3].

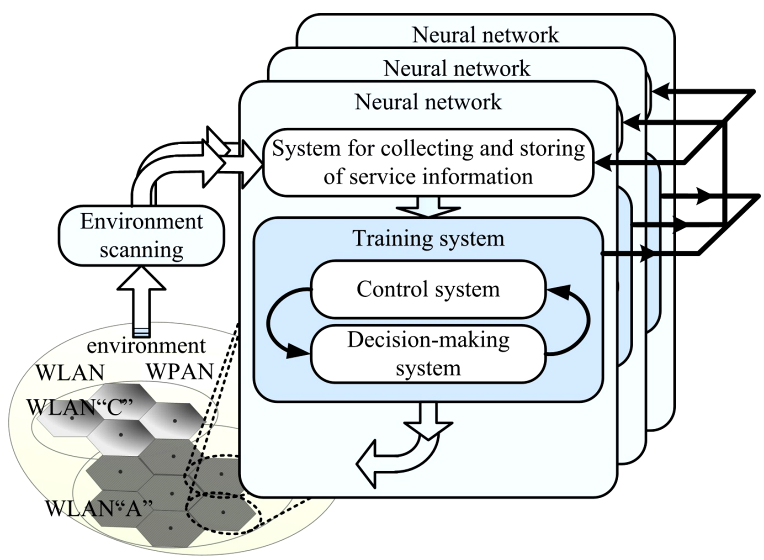

Fig. 1. Architecture of the WRAN environment control using a neural network

Using the inner organization of a network, a provider can set up a billing system inside WRAN or organize a roaming service if it concerns another WRAN. Functions related to user authentication, tariff setting, security, confidentiality, mobility control can also be considered as the parameters of a neural network. The application of an additional neural network makes it possible to predict the load and mutual effect of the parameters on each other. Thus, it is possible to predict the throughput of both AP (Access Point) and the entire network, the load over different periods of time, etc. Based on the accumulated data, the neural network should ensure a balanced allocation of resources on the WRAN scale. The given network will strive to provide service to the maximum number of subscribers, to minimize the cases of denial of service at the same time.

A neural network in each WRAN can collect statistics about the state of the environment to analyze and estimate parameters in order to optimize system performance, which can be based on prediction using a neural network or other methods. Information can be expanded with additional determining components to provide additional data specifically related to security, unauthorized access, the influence of other WRANs. The neural network employs measurement results to generate a local control solution and regulates performance of the entire WRAN system.

The interaction of WRAN under control of a neural network is an important aspect in the construction of multi-cluster systems. Interaction at the trunk level, requirement to the throughput, mutual influence on each other were not considered.

The architecture of the WRAN environment control using a neural network is shown in Fig. 2 in detail.

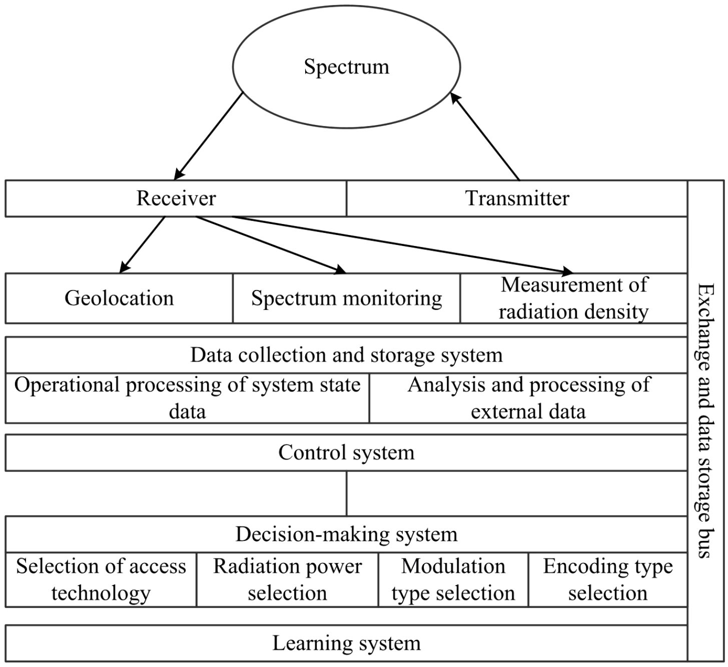

Fig. 2. Flow chart of the algorithm to control the environment using a neural network

The given system includes the following functional blocks:

– *Transmission and reception unit*. Serves to receive and transmit information.

– *Unit of geolocation, spectrum monitoring and measurement of radiation level*. It is intended for positioning of the system based on GPS or GLONASS, analyzing the environment and signal power level.

– *Data exchange bus*. This unit covers all levels of the environment control operation. It is intended to exchange information of network elements with a subsystem of storage and collection of service information.

– *Unit for storing and processing of service information*. In fact, this element is an object-relational database. Its main purpose is operational processing, analysis and structuring of external data and network state data. Each function unit has an individual circuit, which can be accessed for reading by any element of the system. However, only a functional unit, which includes both the circuit and the control subsystem, can perform recording.

– *The control system unit, the learning subsystem, the decision-making subsystem* are the basic elements and they are described in more detail.

4. 1. A cognitive radio network control system

Analyzing [12, 13], the system of indirect control is the most widely used. However, identification and control are based solely on the error of the neural network identifier. Given this, it is impossible to guarantee minimization of the error at the output from the entire system. A direct control circuit has been chosen.

Stability and manageability of such MS are discussed in detail in article [13].

In the direct control circuit, parameters of the neural network controller are adjusted in such a way as to reduce directly the error of the E_y output shown in Fig. 3.

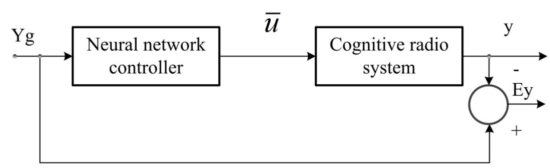

Fig. 3. Direct control circuit

As an objective function, which should be minimized by the controller, the mean-square error is used at the output of the controlled object [4]:

$$E_Y = \frac{1}{2}(y_g - y)^2, \qquad (1)$$

where E_Y is the objective function, Y_g are the input parameters of the network, y are the output parameters of a cognitive radio system.

In the method that employs NN, there are no constraints to the linearity of the system. This method is effective under noise conditions and provides real-time control upon completion of learning. This satisfies conditions for constructing the cognitive radio systems. Neural network MSs are more flexible to adjust to real conditions, forming the models that are fully adequate to cognitive systems, not containing constraints related to the construction of formal systems. In addition, neural network MSs not only implement standard adaptive control methods, but also propose their algorithmic approaches to a number of tasks. Solving such tasks can be difficult, because of unrealizability, since for the NNs only their correlation is important.

4. 2. Development of a training subsystem to control the environment of a cognitive radio system using a neural network

The training subsystem consists of a hybrid form of error correction and the accumulation of experience from past iterations in the repository of properly classified examples:

$$\{(x_i, d_i)\}_{i=1}^{N}, \tag{2}$$

where x_i is the input vector, d_i is the desired signal corresponding to the input vector.

The given algorithm includes two components:

– a criterion used to determine the vicinity of sample x_{test};

– a training rule applied, for example, from the vicinity of the selected sample.

In the simplest form, an example closest to the test case is included in the vicinity. For example, sample $x_N \in \{x_1, x_2, ..., x_N\}$.

It is considered the adjacent sample x_{test}, if the following condition is satisfied:

$$\min_i d(x_i, x_{test}) = d(x_N, x_{test}), \tag{3}$$

where $d(x_i, x_{test})$ is the Euclidian distance between the x_i, and x_{test} samples.

The class to which the closest sample belongs is also considered as the class of the tested x_{test} sample. This rule does not depend on the allocation employed during generation of learning examples.

In [14], a formal study of the rule of the adjacent sample used to solve the task, for example, a problem on the classification of control signals, is given. In this case, the analysis is based on the assumption that signal (x_i, d_i) is independent and uniformly distributed in accordance with the collaborative distribution (x, d).

The given system should be well predetermined and must fulfill the following conditions:

– Existence. For any $x \in X$ input vector, there is an output value $y=f(x)$, where $y \in Y$.

– Uniqueness. For any pair of input vectors $(x, t) \in X$, equality $f(x)=f(t)$ holds when and only when $x=t$.

– Continuity. The mapping is considered continuous if for any $\varepsilon>0$ there exists such $\delta=\delta(\varepsilon)$ that the condition $p_x(x, t)<\delta$ implies that $p_y(f(x), f(t))<\varepsilon$, where p() is the distance between two arguments in the corresponding spaces. The continuity property is also called stability.

Learning is considered as a task of reconstructing of a hypersurface based on a set of points, which can be quite sparse.

Correction of errors implies selection of centers on the basis of self-organization and submission of an error onto the input of the network. For the learning process, it is required to develop a clustering algorithm that divides a given set of data points into two subgroups, each of which must be as homogeneous as possible. For the given situation, we shall use the k-means clustering algorithm. This algorithm can be described as follows:

1. Initialization. We choose random values for initial centers $t_k(0)$. The only requirement for their choice at this step is the disparity of all initial values. The values of the Euclidean norm should, if possible, be minimized.

2. Sampling. We choose vector x from the input space x with a certain probability. This vector is the input for the algorithm at iteration n.

3. Similarity matching. We denote $k(x)$ as the index of the most satisfying (victorious) center for the given vector x. We find $k(x)$ at iteration n, using a criterion of the Euclidean distance minimum:

$$k(x) = \arg\min_k \|x(n) - t_k(n)\|, k = 1, 2, \ldots, m_1, \tag{4}$$

where $t_k(n)$ is the center of the k-th radial basis function at iteration n.

4. Updating. We update the centers of radial basis functions using the following rule:

$$t_k(n+1) = \begin{cases} t_k(n) + \mu[x(n) - t_k(n)], \\ t_k(n) - \text{if not}, \end{cases} \tag{5}$$

where μ is the learning-rate parameter chosen from the range $0<\mu<1$.

5. Continuation. We increase the value of n by unity and return to step 2, repeating the procedure until position of t_k centers changes significantly.

Using this hybrid system, the probability of a signal error, when using the nearest neighbor rule, is two times larger than the Bayes error probability.

4. 3. Decision-making subsystem

Based on incoming external data, the decision-making subsystem must select the access type based on the signal level and control the radiation power, modulation types and coding. Based on the work performed in chapter 4.1, a system that meets all the requirements is a particular case of the radial basis networks – a probabilistic neural network (PNN). Fig. 4 shows a PNN network architecture.

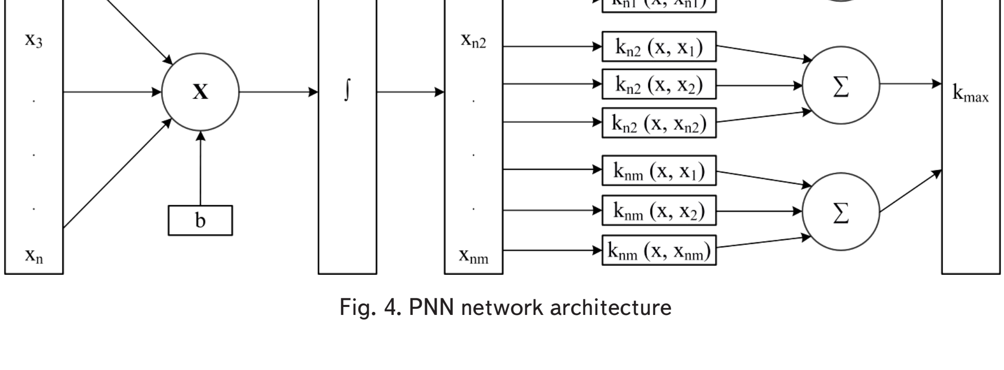

Fig. 4. PNN network architecture

The PNN network architecture consists of two layers. The first layer is based on the radial basis network architecture, but uses the competing layer as the output layer. This layer counts the probability of the belonging of input vector to a particular class. Ultimately, the first layer compares the vector to that class, the probability of belonging to which is higher. The input competing layer does not execute computations and serves to receive and divide attributes of the input vector. The number of neurons of the input layer is determined by the number of attributes of vector X. The pattern layer contains one neuron per each sample of the input vector from the learning sample. That is, for a total volume of learning sample that contains N samples, the sample layer must possess N neurons. The input layer and the sample layer form a fully connected structure.

Let the identified non-linear dependence be represented as an "input-output" sample:

$$(x_i, y_i).1=1,'M, \tag{6}$$

where $x_i=(x_{i,1}, x_{i,2}, ..., x_{i,p})$ is the input vector; y_i is the output of the i-th pair; M is the sample size.

The summation layer contains the number of neurons equal to the number of classes by which the input patterns are divided. Each neuron of the summation layer has connections only with the neurons of the layer of samples that belong to the corresponding class. All weights of the connections of the summation layer in a traditional probabilistic neural network are equated to unity.

The source neuron functions as a discriminator of the threshold magnitude. It indicates which neuron of the summation layer has the maximum output signal. This defines the class to which the provided input pattern belongs. The weights of the neuron connections of the output layer are set so that the neuron of the summation layer with the highest activity value is identified at its output.

During learning, a structure of the probabilistic neural network is formed. The dimensionality of N training sample vectors X_i, $i=1, ´L$ determines the number of neurons and the structure of the incoming layer of the probabilistic neural network. The total size L of training sample X_i, $i=1, ´L$ corresponds to the total number of neurons in the sample layer.

The presentation of each of L samples to the network is accompanied by an indication from the trainer of the number of k-th class to which the incoming sample belongs. The sequence of presentation of learning samples can be any. After the presentation of all L vectors of the learning sample, the structure and parameters of the network are formed in the form of a matrix. After this, the learning process of the probabilistic neural network is completed and the network is ready to determine the tasks set.

Under normal network operation, an input pattern of the unknown X class is entered, which is first normalized, and then multiplied by a matrix of weights and it accordingly activates the neurons of the sample layer. Each neuron in the sample layer shows at its output a certain level of activity $y_i(X)$. Each k-th neuron of the summation layer sums up the equal activities $y_i(X)$ of all neurons of the layer of samples of the k-th class. It shows at its output the overall activity level of the given k-th class $y^k(X)$, k=1, ´M. In addition, the k-th neuron of the summation layer determines which neuron of the summation layer has the maximum output signal $y^k(X)$. Thus, the number of the k-th neuron determines the number of k class, to which the pattern of X belongs with a higher probability.

The influence parameter b is critical for the effectiveness of PNN. The magnitude of b affects the quality of density recovery. It follows from [10] that if the value of b is small, then the radial basis function (RBF) is characterized by a sharp decrease, and the range of input values, to which neurons react, is very small. As the influence parameter b increases, the inclination of RBF becomes smoother, and in this case several neurons respond to the input vector values. The optimal magnitude b is determined by practical means, that is, between the accuracy of description of specific data and the smoothness of RBF.

The activity function of the k-th summation neuron determines the value of the probability of density distribution for the whole k-th class. In general, it is calculated from formula:

$$y^k(X)=\frac{1}{N(2\pi)^{\frac{P}{2}}bp}=\sum e^{\left(\frac{-(x-x_{kj})^T(x-x_{kj})}{2b^2}\right)},\quad k=1,'M. \tag{7}$$

5. Results of examining the improved method to control the environment of a cognitive radio system using a neural network

To simulate a PNN neural network, the MATLAB software package has been selected. In order to determine the two measurable vectors of the input set, four domains of input vectors with a normal distribution law with arbitrary values have been created. By using standard functions of sections "neural" and "Simulink", the resultant vector, included in the existing set and not belonging to the training sample, has been modeled. Such samples can be matched with a connectivity matrix in the form of a sparse matrix that determines the belonging of the first two vectors to one class of the input set, the next two vectors to another class of input set, etc. The resulting arrays assign the learning set. Next, a radial basis network has been formed on the basis of the application of the incoming connectivity matrix, the resultant vector, the mean-square error equal to 0.1, the influence parameter equal to 0.5. As a result, the network is trained, which modifies the weighting coefficients and their displacement in accordance with a sequential increment determined in a practical way. As a result of the network modeling, a connectivity matrix corresponding to the input vector has been formed. Then the array of the connectivity matrix has been converted into indices. Results of the values of the input and output subsets are given in Table 1 and are shown graphically in Fig. 5.

It follows from Table 1 and Fig. 5 that the network has 20 neurons. The network trained for 1200 ms, which is 800 ms (by 1.67 times) faster than the required value according to the IEEE-802.22 standard (2000 ms). The input and output magnitudes of sets have small deviations and, in some positions, are equal to each other, which confirms correctness of the network learning. The network defined 4 groups and two incoming vectors to one of the groups, where their values are shown by asterisks in Fig. 5 (red asterisk – included in the learning set, blue one – not included in the learning set), and the incoming values of data arrays are marked by dots.

Table 1

Result of the work of a PNN network

The first value of the input set *Tc*, units	The last value of the input set *Tc*, units	The first value of the output set *Tc*, units	The last value of the output set *Tc*, units	Weights value, units
0.9422	0.3542	0.9421	0.3532	0.6587
0.9571	0.8212	0.9561	0.8212	2.7821
0.4752	0.1174	0.5752	0.0154	2.6608
0.0991	0.0437	0.0598	0.0430	2.1159
0.1358	0.1699	0.2348	0.1690	4.7856
1.6491	0.2963	1.6491	0.2963	4.9677
1.7317	0.7447	1.7317	0.7447	0.2039
1.5475	0.4890	1.6477	0.1890	4.8169
0.5519	0.9774	1.4509	0.6868	4.6603
1.9474	0.2881	1.5470	0.1835	0.4926
1.2535	1.6251	1.3685	1.7757	4.4364
0.9246	1.2368	1.6256	1.4868	4.8169
1.7801	1.4358	1.7802	1.4359	4.6603
1.7282	1.1043	1.9294	1.3063	0.4926
0.4185	0.9785	0.5085	1.3786	4.4364
0.6328	1.6125	0.5108	1.8116	2.8522
0.8176	1.5328	0.8176	1.5328	2.7421
0.6728	0.8916	0.7948	1.3507	2.5012
0.6510	1.9800	0.6443	1.9390	2.4358
0.9985	1.5474	1.0811	1.4468	0.9975

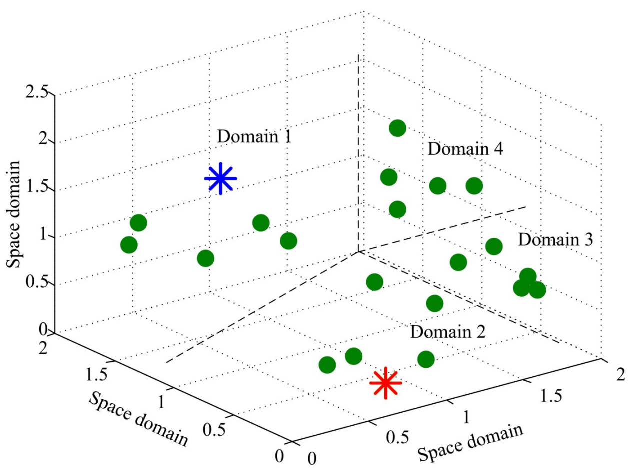

Fig. 5. Result of the work of a PNN network

6. Discussion of results of examining the improved method to control the environment of a cognitive radio system using a neural network

The existing method of the environment control with a centralized controller displays a redundancy of software and technical means of allocation of information flows between the network nodal elements [4]. The improved method was simulated in the MATLAB programming environment and has a smaller volume of programming code, and, accordingly, a less number of the required technical means. This is confirmed by an increase in the network performance by 1.67 times in comparison with the standard of a cognitive radio, which is achieved through the use of parallel processing of information.

The decentralized method of environment control has a low fault tolerance [5]. The improved method is potentially fail-safe. Under adverse network simulation conditions, the performance of the proposed method deteriorates insignificantly. With an incorrect or missing neuron or its connection, retrieval of recorded information is difficult. However, taking into account the distributed nature of information storage in a neural network, it can be stated that only serious structure damage of a neural network can significantly affect its performance, which has been confirmed by theoretical considerations [13] and simulation results. Therefore, a decrease in the quality performance of the neural network occurs slowly.

In the self-organizing method of control, there is no accumulation of the right and wrong decisions taken [6]. The improved method has a separate data collection and storage system, in addition, based on this information, a separate system makes a decision.

In multi-agent systems, there is a decrease in performance and an increase in the cost of deploying the radio system through an increase in the scalability [7]. In the improved method, there are no mechanisms for the implementation of a dynamic change of the environment. This method possesses ability to adapt to the environment changes. In particular, a probabilistic neural network, trained to operate under certain conditions, can be quickly re-trained to operate at insignificant fluctuations in the input parameters. Employing the capability to learn on a lot of examples, the improved method is able to solve tasks with unknown conditions in the development of a situation and unknown dependences between input and output data. Traditional mathematical methods and expert systems are ineffective in such cases.

The given method also makes it possible to work in the presence of a large number of uninformative, noise input signals. There is no need to do their preliminary sorting, the improved method is capable of determining their suitability for the problem and, if necessary, of discarding them.

The time spent on learning, that is, the fact that a network can initially work with errors and some deviations, can be noted as a disadvantage of the improved method. A change is also possible in the structure of a neural network depending on the change in WRAN architecture.

Present research can be considered as the introduction of learning functions into the IEEE 802.22 standard by describing the architecture of a cognitive radio system using a neural network. In addition, the research results could be applied when modeling an IEEE 802.22 network, and as an element during physical deployment of WRAN.

In the future, in order to improve characteristics of WRAN environment and trouble-free operation, it is necessary to continue research related to the development and improvement of methods to control the environment of a cognitive radio and neural networks. In addition, separate subsystems of the proposed architecture are the subjects for further studies.

Results obtained in the present work are of independent value and could be used both for the modernization of existing WRAN control systems and in the development of promising intelligent radio systems.

7. Conclusions

The developed architecture of WRAN environment control using a neural network exhibits a special feature in that a neural network is located at each base station (BS) and interacts with other WRANs in line with the IEEE 802.22 standard. The network surrounding may include other WRANs, with which it can interact. These interactions can include data sharing and resource allocation coordination. Due to this, adaptation to changes in the environment and an increase in the performance speed by 1.67 times are provided. This established fact can be explained by that such an architecture is better aligned with parameters established by the IEE802.22 standard, in comparison with other existing methods.

The developed flow chart of the environment control algorithm using a neural network possesses a feature demonstrating that neural network control systems are more flexibly tuned to real conditions, forming the models that are fully adequate to cognitive systems. This algorithm applies a hybrid learning system. In addition, the developed flow chart of the environment control algorithm using a neural network is implemented on the basis of a particular case of radial basis networks – a probabilistic neural network. Due to this, a Bayes error probability is reduced while the network performance is increased. This established fact can be explained by that the hybrid learning form and a PNN network have been employed.

PNN simulation as a decision-making subsystem in the environment control of a cognitive radio system has the feature showing that the network has one competing layer and one layer for receiving and dividing the attributes of the input vector. Due to this, a small number of neurons of the network are applied and its learning ability is fast. This fact can be confirmed by that the neural network, chosen in a practical way, is better suited to the tasks set.

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