meet the requirements for electromagnetic compatibility, resistance to climatic and mechanical influences. Introduced 2012–09–01. Moscow, Standardtinform Publ., 2012. 28 p.

6. Kandyrin Yu. V., Kamaev V. A., Kononov M. Ye., Shkurina G. L. Strukturirovanie variantov v elektronnykh spravochnykh sistemakh vybora [Structuring options in electronic reference systems of choice]. *Prikaspiyskiy zhurnal: upravlenie i vysokie tekhnologii* [Caspian Journal: Management and High Tekhnologies], 2015, no. 2 (30), pp. 93–104.

7. Kechiev L. N. *Proektirovanie pechatnykh plat dlya tsifrovoy bystrodeystvuyushchey apparatury* [Design of printed circuit boards for high-speed digital hardware], Moscow, OOO «Gruppa IDT» Publ., 2007. 616 p.

8. Kolganov A. A. Avtomobilnye okhrannye sistemy. Istoriya, sostoyanie i perspektivy [Car security systems. History, current state and prospects]. *Sbornik trudov VI Mezhdunarodnoy nauchno-prakticheskoy konferentsii uchashchikhsya i studentov* [Proceedings of the VI International Scientific and Practical Conference of Pupils and Students], Protvino, Upravlenie obrazovaniya i nauki Publ., 2013, part 2, pp. 791–794.

9. Kolganov A. A., Lisitsyn I. Yu. Analiz elementnoy bazy dlya realizatsii sovremennoy avtomobilnoy radiookhrannoy sistemy [Analysis of components for the implementation of modern automotive systems radiosecurity]. *Kachestvo. Innovatsii. Obrazovanie* [Quality. Innovation. Education], 2015, no. 8, pp. 36–44.

10. Kofanov Yu. N. *Avtomatizirovannaya sistema ASONIKA v proektirovanii radioelektronnykh sredstv* [Automated system ASONIKA in the design of electronic tools], Moscow, Moscow Institute of Electronics and Mathematics Publ. House, 2012. 58 p.

11. Nikolaev P. A. Ustoychivost avtomobiley k elektromagnitnomu vozdeystviyu [Vehicle Stability to electromagnetic interference]. *Tekhnologii EMS* [Technologies of EMC], 2014, no. 4, pp.72–75.

12. Prilozhenie 1 k resheniyu GKRCh ot 7 maya 2007 g. № 07-20-03-001 [Application 1 to the decision of the SCR by May 7, 2007 no. 07-20-03-001]. *Minkomsvyaz Rossii* [Russian Ministry of Communications]. Available at: http://minsvyaz.ru/ru/doc/?id_4=302 (accessed: 10.10.2014).

13. *Prilozhenie 3 k resheniyu GKRCh ot 7 maya 2007 g. № 07-20-03-001. Ustroystva okhrannoy radiosignalizatsii* [Application 3 to the decision of the SCR on May 7, 2007 no. 07-20-03-001. Radiosignalizatsii security devices]. Available at: http://minsvyaz.ru/common/upload/docs/20070619163831OU.doc (accessed: 10.10.2014).

14. *Prilozhenie 13 k resheniyu GKRCh ot 7 maya 2007 g № 07-20-03-001. Telematicheskie ustroystva na transporte* [Application 13 to the SCR decision of 7 May 2007 no. 07-20-03-001. Telematics devices for transport]. Available at: http://minsvyaz.ru/common/upload/docs/20080625085835Jg.doc (accessed: 10.10.2014).

15. Aminev D., Azizov R., Uvaysov S. Recommendations for the choice of antenna trans-ceivers of decentralized self-organizing networks. *Innovatsii na osnove informatsionnykh i kommunikatsionnykh tekhnologiy: materialy mezhdunarodnoy nauchno-tekhnicheskoy konferentsii* [Innovations Based on Information and Communication Technologies. Ptroceedings of the International Scientific Conference], Moscow, Moscow Institute of Electronics and Mathematics Publ. House, 2013, pp. 480–481.

16. Kolganov A., Sviridov A. GSM modules in energy efficient M2M-systems. *Innovative information technologies. Materials of The International Scientific-Practical Conference*. 2014, part 3, pp. 333–337.

USING CONNECTIONIST METHODS IN THE DIAGNOSIS OF NETWORKED CONTROL SYSTEMS: PPLICATION TO THE OPERATION OF A WIND TURBINE

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For support of stable exploitation of various equipment types very often it is used computer applications, including special Computerized Maintenance Management Systems (CMMS). The diagnostic operations for equipment are the most important part of these CMMS. Often, the important aim of CMMS application is differentiating of various types of equipment failures. It is especially difficult to make it at remote diagnostics of equipment, located at long distances. Results of diagnostics can be used for decision-making about management of equipment operating modes (regimes), estimates of need of repair operations carrying out and so forth. Networked Control Systems (NCSs) are implied in all spheres of human activity. In the field of industrial production the development of those new technologies have been led to emergence of several categories of industrial local area networks (field networks, cell networks, control and monitoring networks) and several communication standards (Modbus, Profibus, FIP, Profinet and so fort). To improve quality of diagnostic results, it is necessary to know the parameters dynamics for various components of the system. It will allow, in particular, differentiating faults of control and communication systems, used for remote diagnostics and management of equipment. The main aim of this work – automating process of failure analysis for remote actuator of wind turbine, located on remote site. This aim is reached due to application of NCS, using connectionist methods. Authors utilized neural networks, which had the homeostasis property.

Keywords: wind turbine, wind generators systems simulator; network control systems, connectionist methods, neural networks, homeostasis, internal environment, external environment

ИСПОЛЬЗОВАНИЕ МЕТОДОВ ИСКУСВЕННОГО ИНТЕЛЛЕКТА В ОБЛАСТИ ДИСТАНЦИОННОЙ ДИАГНОСТИКИ РАБОТЫ АЭРОГЕНЕРАТОРА

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Очень часто, когда нужно выполнить техническое обслуживание оборудования, используется программное обеспечение автоматизированных систем управления техобслуживанием (CMMS). Управляемые через сети системы (SCR) сейчас присутствуют во всех сферах деятельности человека. В области промышленного производства появление новых технологий привело к возникновению локальных промышленных сетей следующих категорий: полевые сети, цеховые сети, сети контроля и управления. Кроме того, было разработано несколько специальных стандартов связи, включая Modbus, Profibus, Fip, Profinet и др. Цель данной работы – решение задач автоматизации анализа отказов ветроэлектрогенераторов, вырабатывающих электроэнергию за счет силы ветра. Рассматриваемые задачи относятся к области дистанционной диагностики (теледиагностики). При этом в разработанной авторами системе мониторинга используются методы искусственного интеллекта, основанные на алгоритмах работы нейронных сетей, обладающих свойством гомеостазиса; коннективистских методов.

Ключевые слова: ветроэлектрогенератор, симулятор ветроэлектрогенератора, управляемые через сеть системы, методы искусственного интеллекта, дистанционная диагностика, нейронные сети, гомеостазис, внутренняя среда, внешняя среда

Introduction. With the development of automated systems and electronics (Actuators Sensors Interface Of Communication Circuits - ASICs), the reducing of costs and the current need to better manage of production system, that receive data related to an application as soon as possible, consult, control or modify the parameters of a remote application have emerged new wiring and communication technologies among the various components of automation. Also they ensure the diagnosis or maintenance of remote actuator.

Nowadays Automated Production System (APS) has important features which include integration of computation, control, and communication in a reliable system that can increase the performance of the process. The peer-to-peer architecture, which can connect the central computer or programmable controller (PLC) to sensors and actuators of the installation depending on whether you chose automation oriented to «system» or to «problem», is no longer sufficient because of the complexity and physical features increase of the latter. The introduction of the architecture of common bus communication network allows optimize the reliability, efficiency, and flexibility of these applications thus solving the problem of higher cost – by reducing time of implementation and maintenance.

The interest to the study of NCS (Networked Control Systems) is not new [3, 12, 15, 19]. The main characteristic of NCS is the information (the set point, the output signal, the control laws) which is exchanged between various components of the system (preactuators, actuators, sensors, and controllers) through a communication network.

The key problem of NCS monitoring is to detect first faults, affecting at the whole system and also to distinguish faults of communication channel (congestion or collusion of information, loss of data, and delay in the communication) from those of the target driven or controlled. In this area there are also several important works, such as Nilson [16] and Zhan et al. [21].

The aim of our work is to automate the failure analysis of remote actuator by applying telediagnosis of NCS with the usage of connectionist methods (known as neural networks). This methodology is applied to operation control of wind turbine, located on isolated site. The structure of this paper is the following: at first it is presented the study of environment for networked controlled systems and its specificities; at the second step it presents the transmission network; at the third step it has been analyzed the results of our simulation; finally a conclusion is derived.

Environment study system controlled network. NCS is a control system in which the control loops are closed through a communication network – as shown in the block diagram of figure 1.

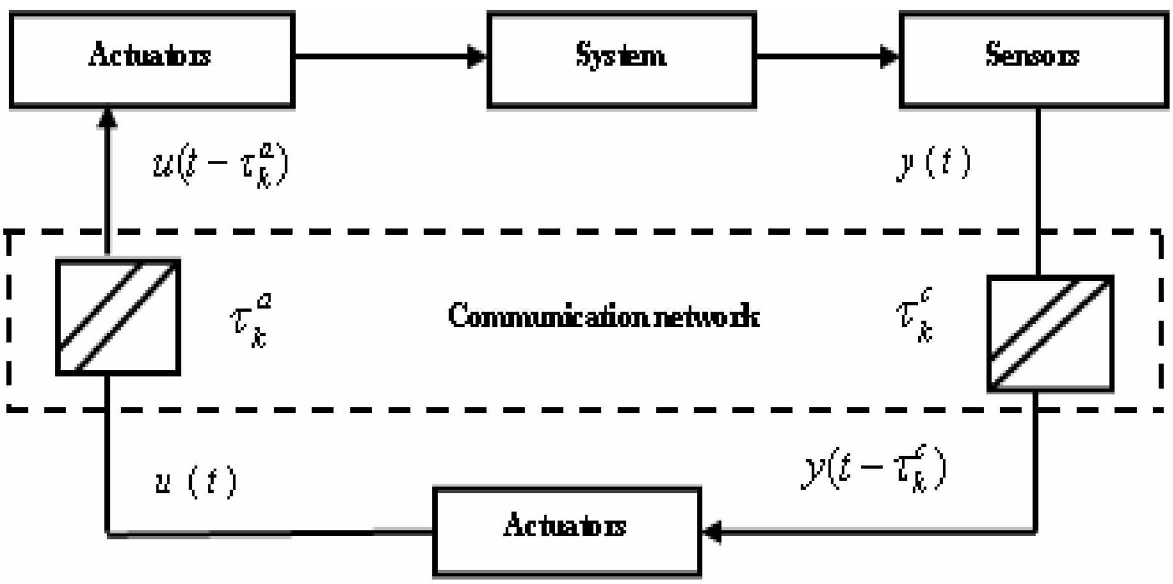


Fig. 1. Block diagram of a conventional system controlled network

For such system, the data arrive from the sensors to the controllers with a delay τ_k^c, generated by the communication network and controllers, and reach the actuators with a delay τ_k^a induced by the network controllers and actuators. The input control signals $u(t-\tau_k^a)$ and output signals $y(t-\tau_k^c)$ have respective delays of τ_k^a and τ_k^c. These delays may influence the performance and robustness of NCS components and can lead to significant degradation of control or diagnostic effectiveness of entire system [4, 13].

Control and diagnosis of NCS are based on dynamic models with a delay. Characteristics depend on several parameters such as transmission protocol, length of the network, network load and interconnection equipment of various system devices. Currently, the modeling of NCS can be subdivided into three categories (fig. 2): from modeling 'tools of physics and mathematics (knowledge models); modeling tools using industrial data (logic models); modeling tools from mathematics learning (models without a priori).

The paper refers to a combination of knowledge models of actuators (generator coupled with a wind turbine) obtained by the deterministic method in direct chain of system command, and in the feedback chain the «model without a priori» method.

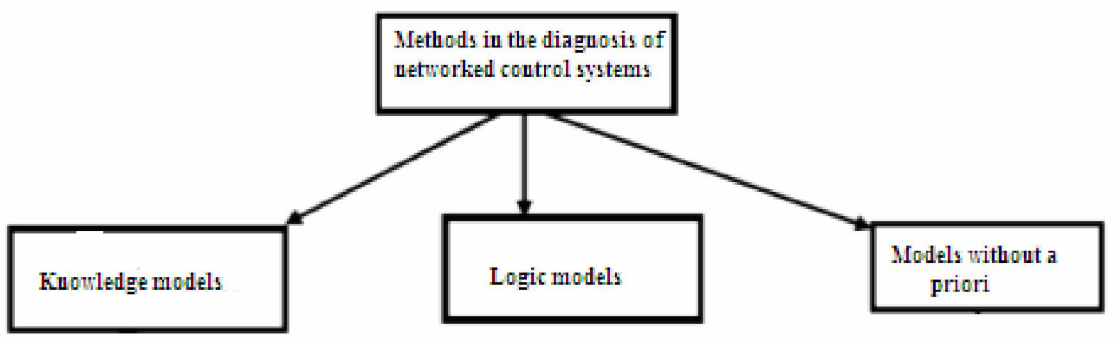


Fig. 2. Classification of methods of NCS diagnosis

The learning environment of networked control systems is used in this work and is named as NNWinTurbLab (Wind Turbine Neural Network Laboratory) - it is far from being a CMMS in a classical sense. We developed a wind simulator with a convenient for usage graphical interface. The NNWinTurbLab allows the linkage between two software types - such as MATLAB and Excel. This linkage is intended to access models of rotary electric actuators, to wind motors (rotors), which can be coupled to obtain various types of wind turbine, behavior patterns models and wind energy production exploration models implemented with MATLAB with its Simulink component [8, 9, 14]. This simulator has the ability to use the remote switch CODIS, allowing a remote equipment monitoring and control, providing a usage of remote diagnostic systems based on neural networks with connectionist methods, utilizing homeostasis.

In the development of laws for controlling systems and processes, the notion of «internal environment» and «external environment» is an essential one. The perfect machine, to which the control engineer tends to mimic in recent years through its models, being human. It was admitted in the late 19-th century by the famous assertion of La Mettrie and Cabanis brain secretes thought as the liver bile, «that the brain is the control center of the body» [5, 8].

This concept of «internal» and «external» environment expresses the correspondence between a living organism, a living body, and an internal environment that ensures the biological unity of the animal and gives its autonomy in the external environment [5].

The principle of the survival or the conservation instinct, that animates all living things, is expressed by the need for a constant of this internal environment which is called homeostasis. It reports on the existence of restoring forces whenever requested, under the influence of variations of internal environment to take abnormal values [5]. The two corollaries of homeostasis are stability and adaptability:

- stability, because the constancy of the internal environment means the ability to resist changes in external and internal environment;
- adaptability, which expresses a causal relationship between the perturbations and the regulatory mechanisms, they have caused.

The formulation of diagnosis is fundamentally based on the strength of industrial process to changes in the external and internal environment. Once the level of resistance is weaken or inhibited the causes of this weakening or inhibition would define the diagnosis. The state of homeostasis of industrial system is achieved by the supervised self-organizing properties and universal approximation of neural networks [8], driven by a remote data acquisition device.

The problem of stability and control of NCS has been demonstrated in [18]. However it is the deterministic models of Ye et al [20] developed under the diagnosis of CRS that will hold our attention. It is used in this case a discrete state observer to generate residues from system equations (1):

$$\begin{cases} x(k+1) = \overline{A}x(k) + \overline{B}_0(\tau_k)u(k) + \overline{B}_1(\tau_k)u(k-1) + \overline{B}_f f(k) \\ y(k) = \overline{C}x(k) \end{cases}, \tag{1}$$

where x is the state vector ($x \in R^n$); u – is the input vector ($u \in R^{ku}$); y is the output vector ($y \in R^{ky}$); τ_k is the constant; $\overline{A} = e^{Ah}$ is the state matrix; h is the sampling period; $\overline{B}_i(\tau_k) = \int_{h-\alpha i-1}^{h-\alpha i} e^{Ah}Bdt$ avec$(\mathrm{i} = 0, 1, \cdots m)$ is the input matrix; τ_m is the maximum known delay; τ_k is the delay, imposed between sensors / controllers and controllers / actuators; α_i is the moment when the command u(k-i) arrives at the actuator to the k-th sampling period and $f(k) = \int_0^h e^{A(h-t)}B_f f(kh+t)dt$ with B_f designating the matrix influence of defects; $\overline{C} = C$ is the output matrix.

Expressing the state observer through its gain, we receive the equation (2):

$$\begin{cases} \hat{x}(k+1) = \overline{A}\hat{x}(t) + \overline{B}u(k) + L(y(k) - C\hat{x}(k)) \\ \hat{y}(k) = \overline{C}\hat{x}(k) \end{cases}, \tag{2}$$

where L is the gain of the state observer and:

$$\overline{B} = \int_0^h e^{At}Bdt = \overline{B}_0(\tau_k) + \overline{B}_1(\tau_k).$$

The residual *r(k)* is obtained as follows:

$$\begin{cases} r(k) = V(y(k) - \hat{y}(k)) \\ r(k+1) = V(y(k+1) - \hat{y}(k+1)) \\ \quad = V\overline{C}[(\overline{A} - L\overline{C})e(k) - \overline{B}_1(\tau_k)\Delta u(k) + \overline{B}_f f(k)] \end{cases}, \tag{3}$$

where $\Delta u(k) = u(k) - u(k-1)$; $e(k) = x(k) - \hat{x}(k)$ is the estimation error; $r(k)$ is the residual vector and $V \in R^{nxq}$ and orthogonal to $\overline{C}$ $\in R^{nxq}$ is the projection matrix.

From the residue expression of (3) we notice that it depends on both the observation error *e(k)* of the delayed input $\Delta u(k)$ and faults *f(k)*. In case when $\tau_k = 0$, $\overline{B}_1(\tau_k) = 0$ generates the following conditions: *r(k) = 0* which implies *f(k) = 0* and *r(k) ≠ 0* then *f(k) ≠ 0*. In this case the residue signal depends both of a delay and a defect. A study of the sensitivity of residual *r(t)* could identify the parameters that affect it [4, 11].

Ye et al [20] used the space parity for the robust diagnosis of NCS compared to the delay τ_k (a bounded delay) using Taylor approximation property of order 1 which yields the matrix $\overline{B}_1(\tau_k) \approx \tau_k B$. Subsequently this artifact allows multiplying the residual *r(k)* of the delay and *x(k)* to make it sensitive to the actuators defects. In our case, we replaced the Taylor approximation by the universal neural networks approximation. Hopfield's neural network was used in [6]. Hopfield's approach is relatively new, although it uses many known results. According to this approach, the neural system searches for stable states, attractors in its states' space. Neighboring states tend to approach a stable state, allowing the correction of errors, and the ability to complete missing information. The Hopfield network is a content addressable memory: a memorized shape is found by a stabilization of the network, if it has been stimulated by an appropriate part of this form. Hopfield proposed a model able to achieve such properties, based on a network of McCulloch and Pitts [8], all parts of this model are interconnected and the Hebb rule is a learning one [5]. Under such conditions the model can be presented by equation (4).

$$O_j^h = f\left(W_0^h + \sum W_j^h E_J^h\right), \tag{4}$$

where: E is a set of examples to classify; E_j^h is the value of the j-th element of example; W_j^h is the weight value, connecting the j-th input cell to that of decision. W_0^h is the bias – O^h is the response of the decision cell. For example h – T^h is the desired response for example h.

It shows that during the evolution of the network, which tends to approach its steady state, an energy function (5), similar to that of ISING spin glasses, decreases to a local minimum [8]. This analogy allows using of a large number of results from statistical physics to the study of its storage capacity.

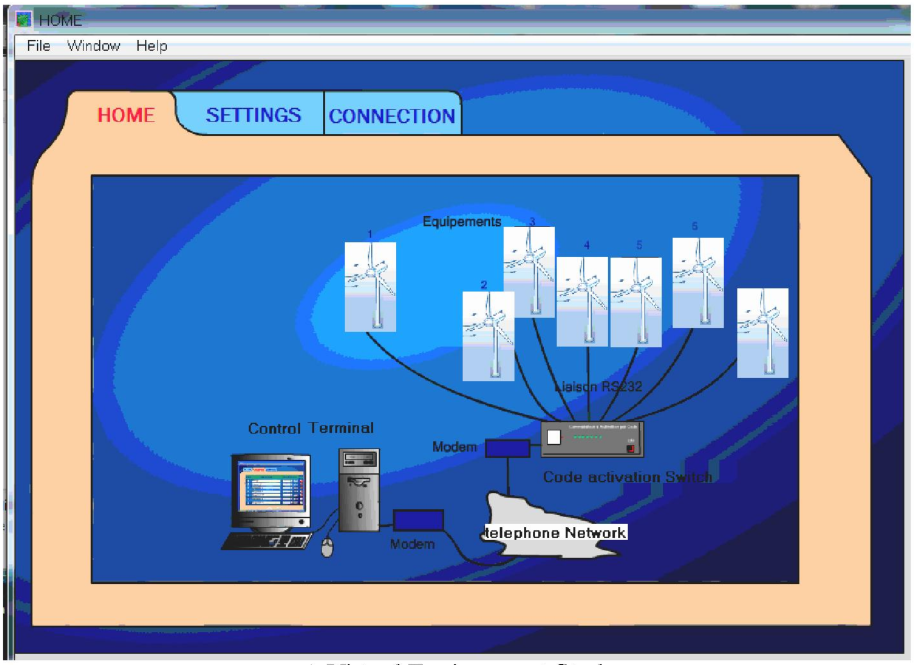
$$H(V) = \sum_i \sum_j T_{ij} V_i V_j \,, \tag{5}$$

where T_{ij} is the connection of a neuron i to a neuron j; $\sum_j T_{ij} V_j$ is the total input of a neuron i; V_i is the state of neuron i at time t.

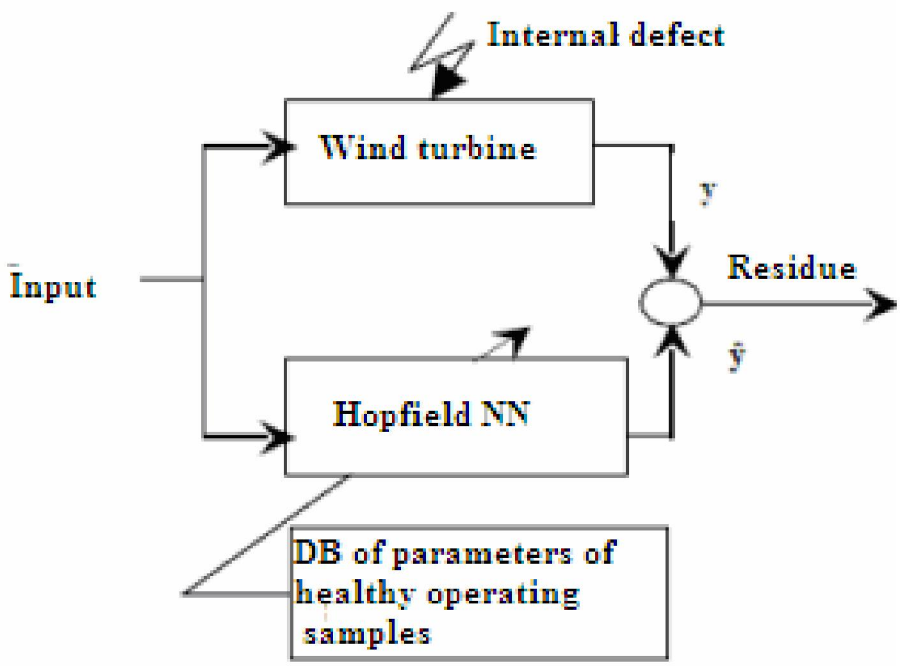
Hopfield's model is a fully connected neural network, operating according to a stochastic dynamic of states. This simple model yields interesting results in self- and hetero-association. In its simplest structure it nevertheless has some shortcomings. They are trash states and catastrophic forgetting [6]. Furthermore the «thermodynamic» approach can offer a dual use of Hopfield networks in optimization problems and classification by the simulated annealing algorithm. Thus, the problem of local minima finds a solution. The Hopfield network ultimately appears as a fully connected network, whose rule is a unsupervised learning [1, 8, 10].

NCS telediagnosis through NNWinTurbLab virtual environment. To identify defects in a system, an analysis, made by neural networks, must have sufficient number of good working examples of defects to be able to learn from. During the learning phase, the examples which presented to the network input corresponding with diagnoses at the output. The self-organizing network learns to combine the examples shown diagnostics. After training, the network not only recognizes learned examples, but also some similar paradigms, which corresponds to certain robustness with respect to the signal deformation by noises. The major drawback is how to determine a methodology to control inner problems, which are mainly the choice of the structure and size of the network and learning algorithms for a specific problem. However, the main reason for their interest in industrial diagnosis is their ability to learn and remember a large amount of information [10, 17].

The virtual environment study is shown in figure 3. It consists of NNWinTurbLab wind simulator, installed on the «Control Terminal»; a CODIS transmission medium, consisting of two modems; the switch activation code, developed by us as a part of this work; data acquisition interfaces from the sensors, associated with wind turbines from 1 to 7 – as shown in figure 3. The NNWinTurbLab simulator is also installed on the computers thereby (1) generating examples for the neural network learning; (2) simulates various types of defects.



a) Virtual Environment Study



b) Virtual Environment structure

Fig. 3. Virtual environment for an NCS study and diagnosis

The graphical interfaces of NNWinTurbLab. Each NNWinTurbLab GUI consists essentially of menu bar, a toolbar, links to the various tabbed pages, that describe the relevant models and a «Run» button to access them. These models and links are shown in figure 4. The knowledge models of the generators developed in MATLAB with its component Simulink are deducted from the generalized model of two-phase to Ferrari-Tesla, applied to actual cases by PARK matrices for AC generators [9]. The models, presented in the turbine wind simulator, are implemented with a multilayer neural network using a learning algorithm, based on gradient descent of Levenberg-Marquardt method [8] for their regulation, or a neural predictive controller type NARMA-L2 (Non-Linear Autoregressive Moving Average) [10]. The simulator also allows modeling of the wind farm to assess its potential, using a neural network, the Hopfield network.

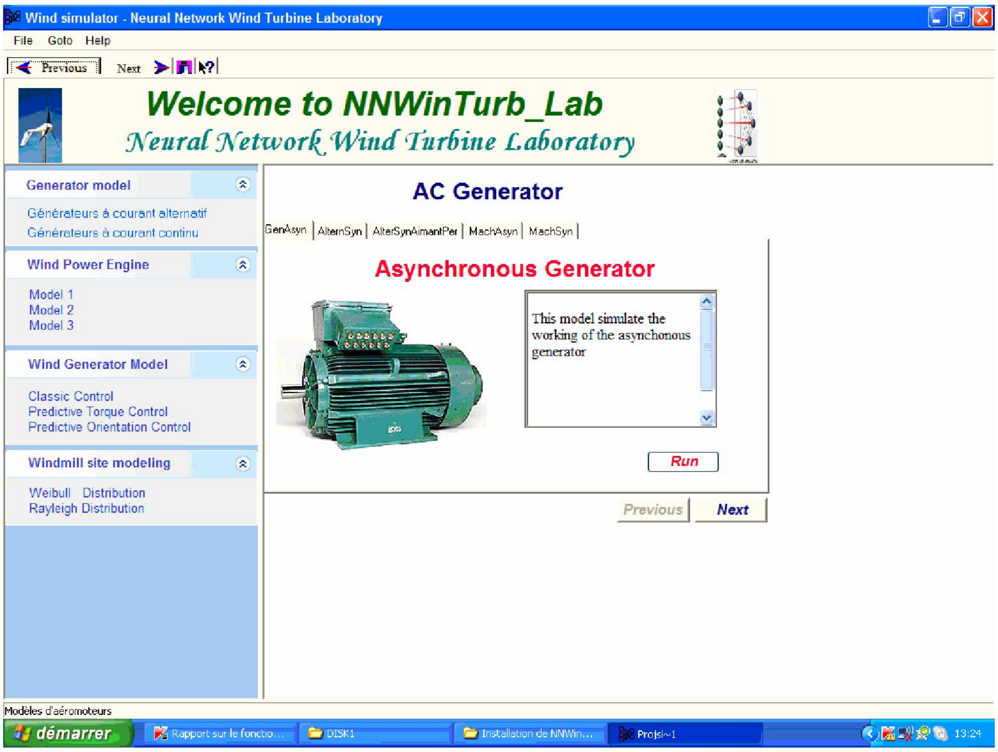
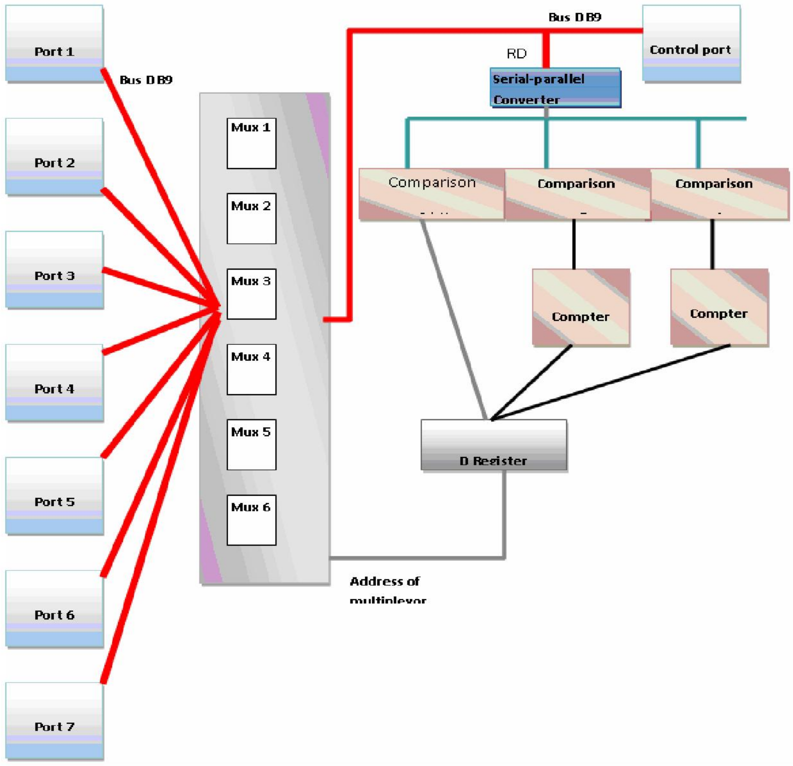


Fig.4. The GUIs NNWinTurbLab

Linkage of MATLAB, Excel and Circuit Maker in NNWinTurbLab. The linkage is essential for communication between the GUI and various software types. We implemented functions DDE (Dynamic Data Exchange) and COM (Component Object Model) of the Windows platform for the exchange of data, stored in memory. To establish this link, we have used the COM model to automate and to make exchanges more secure. Automation implements the COM protocol that defines how an application accesses an object residing in another application or DLL. An automation controller is a client application that controls an automation server via one or more objects provided by the server that implements the IDispatch interface [2, 14]. The graphical interface (a client) handles the automatic loading of MATLAB, Excel and Circuit-Maker (servers) at an application startup. The communication channel is then established and the data exchange via COM functions, built into MATLAB, Excel and Circuit-Maker (*Execute* namely) [2].

Description of the switch CODIS. The code activated switch is a device that is used to select local or remote equipment, which needs to be controlled. It has several communication ports on which equipment will be connected for remote monitoring, and a control port – to be connected either directly to the control computer or (through a modem) for remote control. The switch has seven DB9 ports – inputs, on which it is connected the equipment (computers with installed NNWinTurbLab) and an output, which is obviously connected to the transmission line through a modem. The output also uses a DB9 port. The switch operates on an external power supply of 9 Volts. Then an integrated controller regulates the voltage at 5 V. It is virtual, because it is fully developed under the Circuit Maker. Its structure and graphical interface developed in Visual Basic are represented in figure 5.



a) Material Structure of CODIS

b) CODIS GUI

Fig. 5. Structure and physical GUI of CODIS

Through the switch two types of data pass: the data exchanged between the selected device and the controlling terminal; the control data for the switches. All these types of data are encoded in ASCII. The switch needs to analyze the received characters and to determine the type of data, to which the equipment belongs. To resolve this problem and to increase the reliability of the switch, it accomplishes a specific action, based on a specific received code - as listed in table 1.

Table 1

Codes of connection and disconnection by CODIS

Actions	Hexdecimal Codes
Port N° 1 Connection	0040 0040 0040 0040.0040 0040 0040 0040 0031
…	…
Port N° 7 Connection	0040 0040 0040 0040.0040 0040 0040 0040 0031
Port N° 1 Disconnection	005E 005E 005E 005E 005E 005E 005E 005E0031
…	…
Port N° 7 Disconnection	005E 005E 005E 005E 005E 005E 005E 005E0037

Results and the analysis. Now the imperative is to find the alternative sources to fossil energy ones. In this direction there is a growing enthusiasm for wind energy. Most wind turbines generators, that are converters of mechanical energy of wind into electricity, are asynchronous machines. In such devices multiple failures can occur. They can be predictable or untimely, mechanical or electrical. Their causes are diverse and can be classified into two main families. (1) External failures: mechanical (load torque pulsation, overload incorrect installation), environmental (temperature, humidity, dirt, salinity); electrical (transients, unbalance, voltage fluctuation). (2) Internal failures: mechanical (friction stator-rotor eccentricity, bearing defects, displacement of the windings); electrical (stator faults and rotor, insulation faults) [7].

The simulated faults in this paper are the rotor defects. The optimal approach possible to simulate a bar (or a broken ring portion) is artificially increasing of the value of the resistance of the bar (or ring portion) by a sufficient factor to extent that the current flowing through it is as possible close to zero in a steady state (a cracked bar can be taken into account for an example).

The structure of the Hopfield network, implemented for the treatment of various data consisting of the residues generated using equation (3), by classification is summarized in four tables. In table 2 classification is done by network architecture.

Table 2

Classification by network architecture

Designations	Values
Number of neurons in the hidden layer	21
Sampling interval (in seconds)	0,0001
Number of inputs	3
Number of Outputs	3

Table 3 is based on classification of data, used for network learning.

Table 3

Classification of data, used for network learning

Designations	Values
Number of elements in the training and validation set	200
Maximum value of the input	30
Minimum value of input	1
Maximum time interval (in seconds)	1
Minimum time interval (in seconds)	10^{-5}

Table 4 used learning parameters.

Table 4

Learning Parameters, used for network classification

Designations	Values
Number of iterations	100
Output Activation function	Stochastic
Learning algorithm	Adaptive back propagation

The performance of this neural architecture is given by the parameters in table 5.

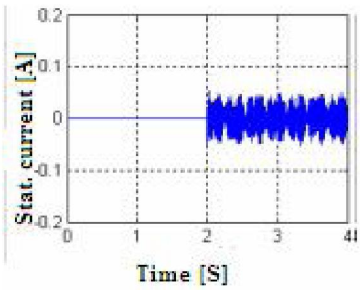
Table 5

Performance parameters of neuronal classifier

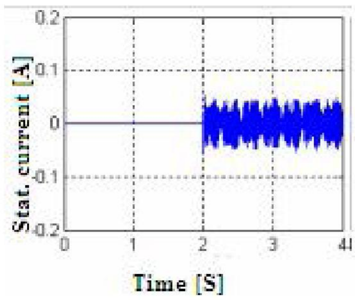
	Accuracy	Rel. Entropy
All	0,594	0,232
Train	0,610	0,228
Test	0,558	0,241

This table shows that the used network is a Hopfield network. The key performance indicator is the relative entropy (Rel. Entropy). It can be noted, that the test has an accuracy rate of 94,4 % compared to learning examples. So the network implementation decreases the entropy.

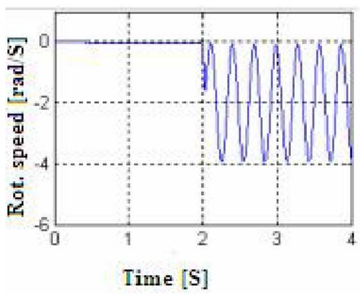
The results, obtained by the virtual environment study described above for the simulation of malfunctions due to broken bars, are summarized in Figure 6.



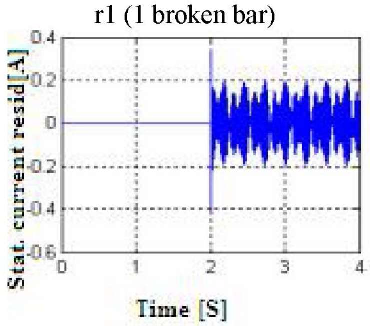
a) Residue of stator current r1 (1 broken bar)



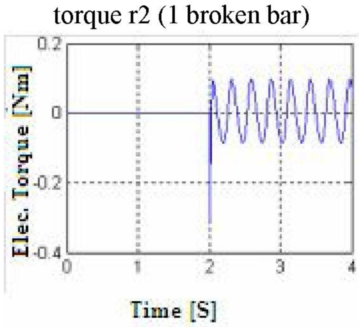
a) Residue of electromagnetic torque r2 (1 broken bar)



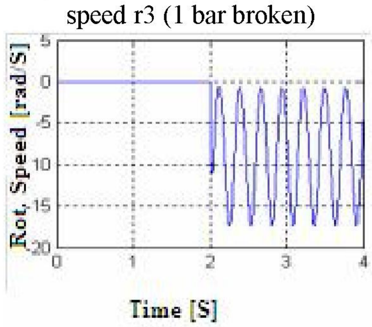
a) Residue from the rotational speed r3 (1 bar broken)



b) Residue of stator current r1 (3 broken bars)



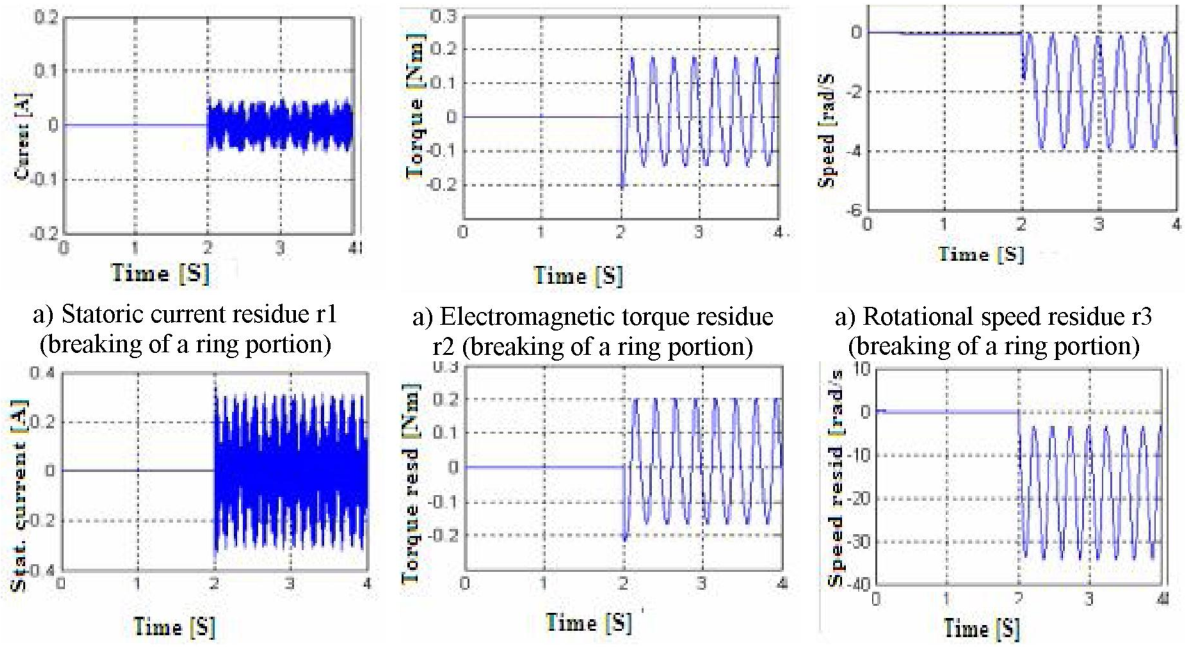
b)-Residue of electromagnetic torque r2 (3 broken bars)



b) Residue from the rotational speed r3 (3 broken bars)

Fig.6: The residues, generated by the breaking of one bar (cases «a») or 3 bars (cases «b»)

The curves in figure 7 represent the residues, generated by the system during the break of a portion or portions of two rings.

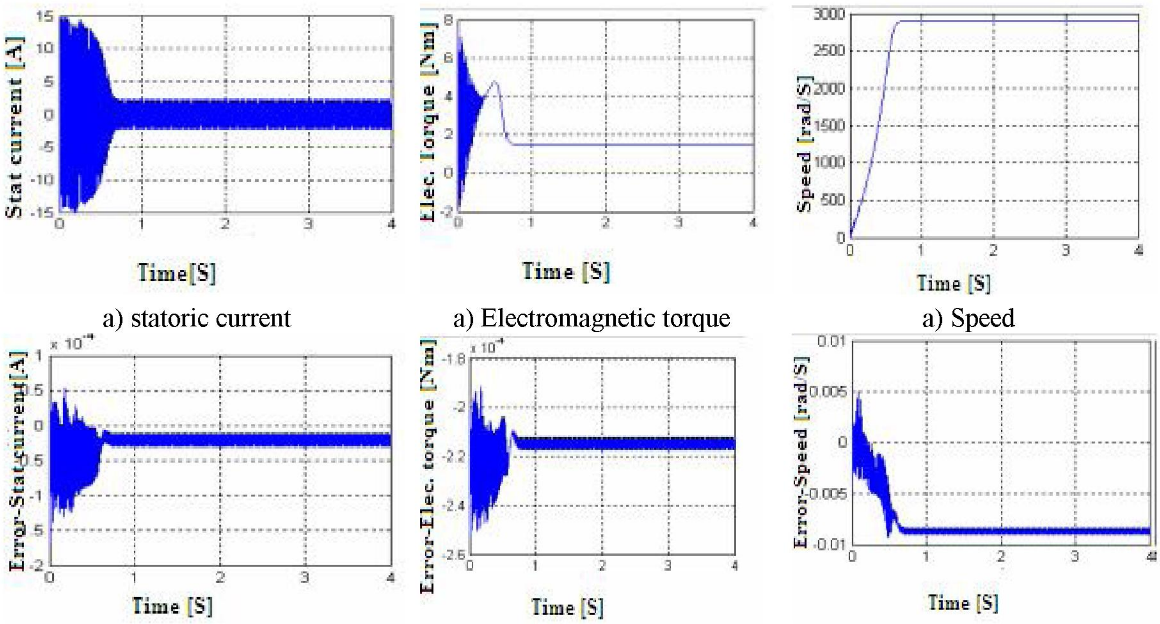


a) Statoric current residue r1 (breaking of a ring portion)
a) Electromagnetic torque residue r2 (breaking of a ring portion)
a) Rotational speed residue r3 (breaking of a ring portion)

b) Statoric current residue r1 (breaking of two portions of ring)
b) Electromagnetic torque residue r2 (breaking of two portions of ring)
b) Rotational speed residue r3 (breaking of two portions of ring)

Fig.7. Residues, generated during the breaking of a portion (cases «a») or two ring portions (cases «b»)

It was observed, that the amplitudes of generated residues classes compared to the system characteristics (stator current, electromagnetic torque and generator speed) shown on the figure 8 considered characteristics of normal or healthy operation, increases when the damage increases in each fault category.



a) statoric current
a) Electromagnetic torque
a) Speed

b) Error of the stator current
b) Error of the electromagnetic torque
b) speed error

Fig.8. Characteristics of the wind turbine generator in healthy operation

The classification results of Hopfield neural networks are shown in Table 6.

Table 6

Results of classification of defects by Hopfield network

State of the wind turbine generator	Amplitude of r1	Amplitude of r2	amplitude of r3
Healthy state	< 0,010	< 0,005	< 0,2
1 broken bar	< 0,060	< 0,030	< 4,0
3 barres adjacent broken	< 0,210	< 0,100	< 17,5
1 ring portion broken	< 0,300	< 0,200	< 29,0
2 portions of adjacent rings broken	< 0,350	< 0,215	< 34,5

From table 6 we noted that the usage of network, based on the connectionist calculation and cognitive techniques, not only allows more accurate detection of malfunctions for turbine of generator, but also provide their easier location.

Conclusion. The main purpose of this paper was to show, that connectionist methods are effective in the diagnosis of networked systems – on the example of controlling wind turbine through its electric generator (an induction machine). Such control can lead to improving of performances (in relation to the current level) due to usage of fast Fourier transform (FFT – Fast Fourier Transform) approach to process measurable quantities - such as current and voltage.

The results obtained in this paper can be considered as a contribution to a new approach that can be called «system approach», in particular based on the signal classification. This approach can be called «class-based signal approach» either by the time-frequency representation or by the amplitude or shape of the signal, which is generated in our case. The parameters of this signal are compared to another signal. The results of this comparison characterize stable and healthy operating condition of the actuator.

This new approach in the diagnosis would allow more detailed exploration of the defects (such as those mechanical – breakage of the blades, bearings wear various levels, the asymmetry of the axis of the wind generator) by increasing the number of inputs of the neural network. This increase would result in a proliferation of sensors and certainly would make the system more expensive. However it should be noted, that the expertise would not fail in cases, where it proves necessary to implement such systems diagnostics. This new approach opens the way for the use of remote diagnostics systems in new tools - such as fuzzy logic, the combination of neural networks and fuzzy logic, expert systems and genetic algorithms.

Список литературы

1. Ackley D. H. A learning algorithm for Boltmann machines / D. H. Ackley, G. E. Hinton, T. J. Sejnowski // Cognitive Science. – 1985. – Vol. 9. – P. 147–169.
2. Borland Inprise Corp. Delphi 5, Guide du Développeur. – Avril 1999.
3. Branicky M. S. Styability of Networked Control Systems Explicit Analyis of Delay / M. S. Branicky, S. M. Phillips, Zhang // Procedings of American Control Conference. – 2000. – Vol. 4. – P. 2352–2357.
4. Faraz K. Ould-Bouamama, Intelligent Monitoring of an Industrial Robot / K. Faraz, R. Merzouki // 9th IFAC Workshop on Intelligent Manufactoring Systems. – Szszecin Poland, October 2008.
5. Heeb D. O. The organisation of behaviour / D. O. Heeb. – New York : Wiley, 1949.
6. Hopfield J. J. «Unlearning» has a stabilizing effect in collective memories / J. J. Hopfield, D. I. Feinstein, R. G. Palmer // Nature. – 1983. – Vol. 304. – P. 158–159.
7. Ivanov-Smolenski A. Machines électriques / A. Ivanov-Smolenski. – Moscow : Mir, 1983.
8. Kodjo M. K. Approche connexionniste pour la modélisation et l'optimisation du rendement d'un aérogénérateur : thése de doctorat / M. K. Kodjo. – Octobre 2005.
9. Kodjo M. K. Modélisation de la conversion électromécanique des machines électriques tournantes sous Simulink / M. K. Kodjo, K. Bedja, A. S. Ajavon, A. A. Salami // Journal de la Recherche Scientifique de l'Universite de Lome (Togo). – 2005. – Vol. 7, № 1. – P. 9–24.

10. Kodjo M. K. C. Lishou· Neural networks for predictive control of the mechanism of orientation of a wind turbine / M. K. Kodjo, K. Bédja, A. S. A. Ajavon, R. M. Faye, C. Lishou // JSPI. – 2008. – № 9. – P. 75–85.

11. Lam J. *A* New Delay System Approach to Network-Based Control / J. Lam, H. Gao, C. Wang // Automatica. – 2008. – Vol. 44, issue 1. – P. 39–52.

12. Lian F. Analysis, Design, Modeling, and Contol of Network Control Systems : Ph. D. dissertation / F. Lian. – Departement of Mechanic Engeneering, the Univerty of Michigan, 2001.

13. Malek-Zavarei M. Time-Delay Systems: Analysis, Optimization and Application / M. Malek-Zavarei, M. Jamshidi. – North-Holland, 1987.

14. Mokhtari M., Apprendre et maîtriser MATLAB / M. Mokhtari, A. Mesbah. – Springer-Verlag, Berlin, 1997.

15. Nilson J. Stochastic analysis and Controlof Real – Time Systems with Random Time Delays / J. Nilson, B. Bernhardson // Automatica. – 1998. – Vol 34, issue 1. – P. 57–64.

16. Nilson J. Real-Time Control System with Delays / J. Nilson. – Lund : Departement of Automatic Control, Lund Institut of Technology, 1998.

17. Ondel O. Diagnostic par reconnaissance des formes : application à un ensemble convertisseur machine asynchrone : thèse de doctorat / O. Ondel. – Ecole centrale de Lyon, 2006.

18. Richard J. P. Systèmes Commandés en réseaux / J. P. Richard, T. Divoux. – 2006

19. Walsh G. C. Stability Analysis of Networked Control Systems / G. C. Walsh, H. Ye, Bushnell // Procedings of American Control Conference. – 2000. – Vol. 4. – P. 2876–2889.

20. Ye H. A New Party Space Approach for Fault Detection Based on Stationary WaveletTransform / H. Ye, G. C. Walsh // IEEE Trasactions on Automatic Control. – 2004. – Vol. 49, issue 2. – P. 281–287.

21. Zhan P. Fault Detection of Networked Control Systems with Missing Measurements / P. Zhan, S. X. Din, P. M. Franck, Sader // Procceding of the 5th Asian Control Conference. – 2004. – P. 1258–1263.

References

1. Ackley D. H., Hinton G. E., Sejnowski T. J. A learning algorithm of Boltmann machines. *Cognitive Science*, 1985, vol. 9, pp. 147–169.

2. Borland Inprise Corp. *Delphi 5, Guide du Développeur*, avril 1999.

3. Branicky M. S., Phillips S. M., Zhang Styability of Networked Control Systems Explicit Analyis of Delay. *Procedings of American Control Conference*, 2000, vol. 4, pp. 2352–2357.

4. Faraz K., Merzouki R., Ould-Bouamama Intelligent Monitoring of an Industrial Robot, *9th IFAC Workshop on Intelligent Manufactoring Systems*, Szszecin Poland, October 2008.

5. Heeb D. O., *The organisation of behaviour*. New York : Wiley (1949).

6. Hopfield J. J., Feinstein D. I., Palmer R. G. «Unlearning» has a stabilizing effect in collective memories. *Nature*, 1983, vol. 304, pp. 158–159.

7. Ivanov-Smolenski A. , *Machines électriques* (Volume 2). Edition «Mir», Moscow, 1983.

8. Kodjo M. K., *Approche connexionniste pour la modélisation et l'optimisation du rendement d'un aérogénérateur*, Thése de Doctorat Unique Octobre 2005, ENSI.

9. Kodjo M. K., Bedja K., Ajavon A. S., Salami A. A. Modélisation de la conversion électromécanique des machines électriques tournantes sous Simulink. *Journal de la Recherche Scientifique de l'Universite de Lome (Togo)*, 2005, vol. 7, no. 1, pp. 9–24.

10. Kodjo M. K., Bédja K., Ajavon A. S. A., Faye R. M., Lishou C.·Neural networks for predictive control of the mechanism of orientation of a wind turbine. *JSPI*, 2008, no. 9, pp. 75–85.

11. Lam J., Gao H., Wang C. A New Delay System Approach to Network-Based Control. *Automatica*, 2008, vol. 44, issue 1, pp. 39–52.

12. Lian F. *Analysis, Design, Modeling, and Contol of Network Control Systems,* Departement of Mechanic Engeneering Publ. House, the Univerty of Michigan Publ. House, 2001

13. Malek-Zavarei M., Jamshidi M. *Time-Delay Systems: Analysis, Optimization and Application*, North-Holland, 1987.

14. Mokhtari M., Mesbah A. *Apprendre et maîtriser MATLAB*, Springer-Verlag, Berlin, 1997.

15. Nilson J., Bernhardson B. Stochastic analysis and Controlof Real – Time Systems with Random Time Delays, *Automatica*, 1998, vol 34, issue 1, pp. 57–64.

16. Nilson J. *Real-Time Control System with Delays*, Lund, Departement of Automatic Control Publ. House, Lund Institut of Technology Publ. House, 1998

17. Ondel O. *Diagnostic par reconnaissance des formes : application à un ensemble convertisseur machine asynchrone*, Ecole centrale de Lyon Publ. House, 2006.

18. Richard J. P., Divoux T. *Systèmes Commandés en réseaux*, 2006.

19. Walsh G. C., Ye H., Bushnell Stability Analysis of Networked Control Systems, *Procedings of American Control Conference*, 2000, vol. 4, pp. 2876–2889.

20. Ye H., Walsh G. C. A New Party Space Approach for Fault Detection Based on Stationary Wavelet Transform, *IEEE Trasactions on Automatic Control*, 2004, vol. 49, issue 2, pp. 281–287.

21. Zhan P., Din S. X., Franck P. M., Sader Fault Detection of Networked Control Systems with Missing Measurements, *Procceding of the 5th Asian Control Conference*, 2004, pp. 1258–1263.